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Sociocultural Behavior Sensemaking

State of the Art in Understanding the Operational Environment

Editors
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Gary L. Klein, PhD
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Preface

The events of 9/11 shifted the baseline of life in the United States and beyond. As with the 1941 assault on Pearl Harbor, they unmoored perceptions from long-held assumptions and entire populations struggled to find new ways to understand the world. Many publications describe and document how these events and subsequent conflicts impacted the requirements of the U.S. national security enterprise. Although many of those requirements were for conventional approaches to solving new-found problems, the attacks also prompted an increased call for a sociocultural capability to understand novel cultural environments, anticipate perceptions and behaviors, and identify alternative approaches to influencing those behaviors. While the merit of such a capability for national defense has long been recognized, 9/11 and the conflicts that followed sharpened the appreciation of its value and accelerated both investment and innovation.

The U.S. national security enterprise adapted its research agenda to address the increased demand for improved sociocultural behavior capability. The largest single initiative, led by the Office of the Secretary of Defense, was the Human Social Culture Behavior (HSCB) Modeling Program. Objectives of this six-year (2008–2013) program were derived from key strategic documents, such as the 2006 *Quadrennial Defense Review* and the subsequent *Strategic Planning Guidance* (SPG) (2008–13) study on human social cultural behavior modeling. Objectives were also shaped by further review of sociocultural behavior research efforts across the Department of Defense (DoD) and dialogue with representatives from both research and end-user communities.

One touchstone was the 2008 National Academies Press publication *Behavioral Modeling and Simulation: From Individuals to Societies*. That report served as a foundation for the HSCB Modeling Program Team and the community as a whole. It provided model developers, operational military users of the models and their managers, and government personnel making funding decisions regarding model development a timely snapshot of the field prior to the DoD research investments.

Sociocultural Behavior Sensemaking: State of the Art in Understanding the Operational Environment provides another snapshot, taken at the end of the DoD's HSCB Modeling Program's research investment, a time of numerous advances in the area of sociocultural behavior analysis

and modeling. Although the domain is still nascent and must continue to evolve, this edited volume captures the state of the art following the first decade of change.

One of the core goals of the HSCB program was to develop models and model-based tools that could be transitioned to programs for use by analysts, planners, and operators across the U.S. government. The present book shows the significant progress in closing the research gaps documented in the 2006 SPG study and the advances made since the publication of *Behavioral Modeling and Simulation: From Individuals to Societies*. Each chapter of the present book describes leading-edge research and development in this domain, which, with some further DoD investments, could also be transitioned to active use. Such use would increase our warfighters' ability to leverage a sociocultural behavior capability in their mission planning and operations.

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Dr. Jill Egeth is a Senior Principal Behavioral Scientist with The MITRE Corporation and Department Head of MITRE's Social and Behavioral Sciences department. Her current and recent research interests include understanding and modeling the human/ social/ cultural/behavioral terrain and assessing the nations' pandemic influenza health cognitions and the impact of these cognitions on emergency preparedness and response activities. She held a Lecturer Position with Johns Hopkins University's Advanced Academic programs from 2002 - 2011, where she taught a rotation of four classes: 1) Persuasion Theory, 2) Health Psychology and Behavior Change, 3) Political Psychology, and 4) Psychology of Terror. Prior to joining MITRE, Dr. Egeth was a Science Policy Analyst with the Federation of Behavioral, Psychological, and Cognitive Science, where she engaged in non-profit science policy advocacy on behalf of the nation's behavioral science researchers. She received her doctorate in Health and Social Psychology from Rutgers University and her undergraduate degree from Binghamton University.

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Gary L. Klein, PhD, received his BA in Psychology and his PhD in Cognitive Social Psychology. He is a Senior Principal Scientist in cognitive science and artificial intelligence at The MITRE Corporation. His work has focused on facilitating how people acquire and use information. Currently, he leads a number of projects on using forecasting models that generate graphical depictions of decision spaces to improve decision makers' "option awareness" under deep uncertainty. He was part of MITRE's team providing systems engineering support to the Assistant Secretary of Defense for Research and Engineering's Human Social Culture Behavior modeling program.

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Dylan Schmorrow, PhD, is the Chief Scientist at Soar Technology (SoarTech), where he applies and advances artificial intelligence technologies that can make people better prepared, better informed, and more capable. As a Senior Fellow at the Potomac Institute for Policy Studies he supports the Institute's mission to identify and aggressively shepherd discussions on key science and technology issues facing our society. Dr. Schmorrow retired from the U.S. Navy as a Captain in

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Matthew E. Brashears, PhD, is an Assistant Professor of Sociology at Cornell University, specializing in social network analysis. His research areas include linking cognition to social network structure, examining the effects of error on information mutation and decay, and developing ecological models that connect individual behavior to collective dynamics. He is the sole Principal Investigator on a Defense Threat Reduction Agency-funded project to develop new methods of identifying terrorist groups preparing chemical, biological, radiological, and nuclear attacks. He is also sole Principal Investigator on a National Science Foundation grant exploring the connections between elements of cognition and social network structure. He has published in a number of journals, including *Nature, Scientific Reports*, the *American Sociological Review*, *Social Networks*, and *Social Psychology Quarterly*.

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Samuel E. Buttrey, PhD, received a Bachelor's degree in statistics from Princeton University in 1983. After eight years as a Wall Street computer systems analyst, he returned to graduate school and received MA and PhD degrees in statistics from the University of California, the latter in 1996. In 1996 he joined the faculty of the Department of Operations Research at the Naval Postgraduate School in Monterey, California. He was promoted to Associate Professor with tenure in 2002 and was awarded the Rear Admiral John J. Schieffelin Teaching award in 2004. He has taught courses on probability, statistics, data analysis, operations research techniques for manpower and personnel data, and reliability. Dr. Buttrey has published papers on nearest-neighbor and other classification methods and on applied problems ranging from numismatics and oceanography to human vision. He has also published papers describing his implementations of algorithms in software. His interests include classification, computationally intensive methods, and statistical graphics.

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Brian Kettler, PhD, is Chief Scientist of the Informatics Lab and Lockheed Martin Fellow in Lockheed Martin's Advanced Technology Laboratories (LM ATL). He has over 17 years of experience in leading advanced technology research and development efforts and over 25 years of experience in software engineering. At LM ATL and previously at ISX Corporation, Dr. Kettler was the Principal Investigator (PI) on a number of applied research and development programs sponsored by the Defense Advanced Research Projects Agency (DARPA), Intelligence Advanced Research Projects Activity (IARPA), and the Air Force Research Lab (AFRL), including the DARPA Integrated Crisis Early Warning System (ICEWS), IARPA Collaborative Analyst/System Effectiveness (CASE), DARPA Agent Markup Language, DARPA Control of Agent-Based Systems, and DARPA/AFRL Planning Initiative. As PI he most recently led the technical work of a multi-organizational team for the DARPA ICEWS

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Julio C. Mateo is a Senior Research Scientist with 361 Interactive, LLC. His research focuses on the development of cognitive models, assessment tools, and training programs to enhance the cross-cultural competence of the U.S. Armed Forces. Mr. Mateo's most recent efforts have specifically focused on modeling the multicultural perspective-taking of soldiers in operational environments, developing individualized assessment of cross-cultural ability, and evaluating and transitioning *CultureGear* into the Army training curriculum. Prior to joining 361, Mr. Mateo also conducted research on multimodal spatial displays at the Air Force Research Laboratory and on assistive technologies for individuals with disabilities at Wright State University (Dayton, OH), where he was a National Science Foundation (NSF) Integrative Graduate Education and Research Traineeship Program Fellow in the Learning with Disability PhD Program. Mr. Mateo obtained a Bachelor's degree in Psychology at the Universidad Pontificia de Salamanca (Spain) and a Master's degree in Human Factors Psychology at Wright State University. He is currently pursuing a doctoral degree in Human Factors at Wright State University.

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This book required expertise across a broad set of topics. To make certain that each of the four very distinct book sections – Understand, Detect, Forecast, and Mitigate – received attention from a specialist in that domain, we designated a lead for each section who was responsible for ensuring technical quality and cohesiveness within and among all of the chapters in his or her assigned section. In addition to the Understand section led by co-editor Jill Egeth and the Mitigate section led by co-editor Gary Klein, the other sections were led by Lashon Booker, Jennifer Mathieu, and Les Servi, to whom we extend our appreciation.

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Thank you to everyone who participated in this tremendous effort,

Jill Egeth
Gary L. Klein
Dylan Schmorrow

Introduction to Sociocultural Sensemaking

Gary L. Klein, The MITRE Corporation

Sociocultural behavior goes beyond mere cultural customs and rituals. It includes the common ways that a group of people interpret cause and effect and the mental models of the world that they share. Understanding why people from a different culture react to events the way they do, detecting subtle but significant changes in attitudes, forecasting how a situation will progress in a foreign environment, and effectively planning how to mitigate these cultural reactions requires comprehending those interpretations and mental models. At the core of understanding sociocultural behavior is sensemaking, which Klein, Moon, and Hoffman (2006) characterize as the process of creating understanding in situations of high complexity or uncertainty in order to make decisions. They describe sensemaking as "a motivated, continuous effort to understand connections (which can be among people, places, and events) in order to anticipate their trajectories and act effectively" (p. 71).

Through sociocultural behavior sensemaking we seek to better understand events in the operational environment as well as how to react. Understanding entails accurate situation awareness and option awareness about an environment. Endsley (1995) defines three levels of situation awareness which we can apply to understanding, detecting, and even forecasting sociocultural behavior: (a) perceiving the sociocultural factors and elements in an environment; (b) comprehending the impact of a pattern of such factors on behavior; and (c) projecting future behavior based on this comprehension. Similarly, Klein, Drury, Pfaff, and Moore (2010) defined three levels of option awareness to facilitate mitigation planning: (a) perceiving the relationship between courses of action and their impact on sociocultural behavior; (b) comprehending the effect of sociocultural factors in mediating that impact; and (c) projecting changes in outcomes that will result from changes to action-options based on that comprehension. This book uses these definitions of sensemaking, individual understanding, situation awareness, and option awareness throughout.

This book describes the *state-of-the-art* for sociocultural sensemaking: the most advanced techniques, technology, methods, and theory at this time. Such state-of-the-art capabilities are found mostly in government, industry, and university laboratories – development at the cutting edge, in the pipeline, but not yet packaged for use in an operational environment.

The book is divided into four sections that address the operational processes defined in Schmorrow (2011), which he called “operational capability areas”: gaining sociocultural *understanding* of a new area of operation, *detecting* sociocultural factors and elements in an environment, *forecasting* behaviors, and *mitigating* those behaviors in ways favorable to our operational objectives. Each of these sections of the book contains four chapters, which focus respectively on four classes of technology: data processing, computational modeling, visualization, and training.

These chapters show how the potential impact of these four classes of technology differs across the four operational capability areas. For example, to aid *understanding,* visualizations must depict quantitative and qualitative data in a way that provides situation awareness of a society's structure and the events that engage a society through its social networks. On the other hand, to aid *mitigation,* visualizations must promote option awareness by presenting the landscape of plausible outcomes for each option in a way that enables the user to easily compare those landscapes and choose the most robust option. To support *detection*, data processing must facilitate the collection of information about sentiment, beliefs, opinion, human networks, and target audiences, and collection must be able to operate in otherwise denied or difficult to penetrate areas. After collection, data processing must then enable the transformation of this data into structures that, for example, supply data to the simulation models used in any of the operational capability areas. In performing *detection,* warfighters use models to perform sentiment analysis or to identify previously unknown groups and individuals that espouse terrorist ideologies and variants of current ideologies. Models that support *forecasting* can project the spread of an ideology throughout a region, while those supporting *mitigation* can project how different courses of action may affect adversary decision making. Finally, training technologies must improve people's performance in each of the operational capability areas, while reducing training time and resources. Moreover, training must improve understanding of the full range of sociocultural behavior, including interpersonal skills that are sensitive to local customs, as well as planning and decision making that take local sociocultural mental models into account.

Section One of this book explores how each of the four classes of technologies contributes to understanding by laying down a foundation of knowledge needed prior to initiating operational activities in a given location. Dingwall, Elson, and Moaddel's chapter on data processing examines approaches to collecting behavioral and environmental data under difficult or even dangerous circumstances. Brashears and Sallach's chapter on computational modeling discusses a sampling of modeling techniques in terms of the factors a tool-user should consider when identifying the most appropriate technique to represent and convey sociocultural understanding. The data visualization chapter by Ryan explores not only traditional means of displaying sociocultural data, but also new techniques for visualizing understanding in multi-dimensional space and the challenges presented by big data. Finally, in their chapter on training, Behymer, Mateo, McCloskey, and Abbe describe training tools that promote interpersonal skills by presenting trainees with situations and interactions with simulated people, as well as tools that use multi-media tutorials, real-world imagery, and virtual environments to help end-users develop cultural observational skills.

The chapters in Section Two apply the four technology classes to sociocultural detection: discovering, distinguishing, and locating operationally relevant sociocultural signatures through the collection, processing, and analysis of sociocultural behavior data (Schmorrow, 2011). Irvine's chapter on data processing for detection focuses on transforming surveys, social media, imagery, and video into information needed to identify noteworthy sociocultural patterns. The chapter on computational modeling, by Sanfilippo, Bell, and Corley, describes using computational models to process data signatures and characterize the behavioral patterns of interest in the underlying data. In their chapter, Fricker, Buttrey, and Evans discuss how visualization can make self-evident the sociocultural phenomena users wish to discern. They highlight exploratory data analysis, as well as

simplifications that help focus attention on differences across a data collection or on changes in the data that occur over time. Finally, Glazer, Saner, Barnes, and Pavisic explore the knowledge requirements for conducting a robust sociocultural analysis, and how these requirements determine the methods and designs needed to train and educate intelligence professionals accordingly.

Section Three addresses the process of tracking and forecasting change along multiple dimensions in sociocultural entities and phenomena of interest. In his chapter, Gabbay distinguishes data processing for forecasting from its use for understanding sociocultural systems or detecting sociocultural signatures. In the context of forecasting, he identifies issues related to processing data that must be kept current with actual events in order to update models that help users anticipate changes along multiple dimensions. In this section, each contributor to the computational modeling chapter describes a different type of model for forecasting. The modeling techniques described include results from mixed-method aggregation, forecasting emotions from social media, causal Bayesian models, systems dynamic models, agent-based models, hybrid models, "soft" modeling methods, forecasting of social networks, and "judgmental" forecasts. In his visualization chapter, Lustick then describes how the necessarily complex results of such models can drive the standardized, but still dauntingly complex, data visualizations needed to convey understanding to users. Finally, Sieck's chapter presents the current state of the science and technology related to training in sociocultural forecasting, and identifies gaps that research must bridge to develop capabilities sufficiently for operational settings.

The chapters in Section Four discuss methods for applying the four classes of technology to mitigate the influence of adverse sociocultural behavior in the conduct of a mission. To accomplish this mitigation, commanders must develop, prioritize, execute, and measure courses of action (COAs) grounded in the social and behavioral sciences (Schmorrow, 2011). Moreover, making robust mitigation decisions in today's complex, uncertain environment demands more than situation awareness; decision makers must achieve *option awareness* (Pfaff, Klein, Drury, Moon & Entezari, 2012). Because decision making for mitigation relies so heavily on computational modeling, the data processing chapter by Duong and Pearman centers on the representation of the data that are input, output, and traded between models and the interfaces among the models, noting that interfaces among disparate models can be so complicated that their design is itself an act of modeling. Sliva's chapter on computational modeling examines a sampling of computational approaches that may facilitate COA development, analysis, and comparison. The chapter describes how computational modeling can relieve decision makers of some of the information processing burden, allowing them to synthesize and integrate the models, knowledge, and insights from the understand, detect, and forecast phases of analysis to provide better option awareness. Improving human comprehension of complex data is also the goal of the visualization techniques discussed in Yost's chapter. Yost describes the research to date in this area and promising directions in this nascent area of using interactive visualization to help compare and contrast COAs. The training chapter by Ruvinsky, Hingst, Hoffman, and Kettler focuses on defining the skills (abilities necessary to perform the task) and knowledge (facts, concepts, and principles needed to perform the task) for making effective mitigation decisions. An initial analysis of the functional tasks involved in

mitigation stresses several key training considerations, such as appropriate objectives and ideal training formats (e.g., computer-based training, classroom, or exercise).

We hope that the authors' surveys of state-of-the-art developments will raise the operational community's awareness of sociocultural technical capabilities. We hope they also provide the research and development funding community with a map of technology gaps that merit future investments to transition these capabilities to the field.

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Section One: Understanding

Gaining sociocultural understanding of a new area of operation

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The sociocultural behavior capability areas framework that guides the structure of this book begins its operational cycle with the requirement to understand the sociocultural environment. In order to achieve understanding, analysts, warfighters, and decision makers at all levels need capabilities that support thorough perception and comprehension, grounded in social and behavioral science, of the sociocultural features and dynamics in an operational environment (Schmorrow, 2011).

As noted in the introduction, understanding involves both situation awareness and option awareness of an environment. Endsley (1995) would include understanding the impact of a pattern of sociocultural factors on behavior in her definition of situation awareness, while Klein, Drury, Pfaff, and Moore (2010) would include comprehension of the effects of sociocultural factors on action-outcomes in a delineation of option awareness levels for mitigation planning. The framework that guides this book describes an organizational operational process, rather than the cognitive processing mechanisms of the brain – that is, it delineates a standardized approach to a process that ensures consistent behaviors and approaches across the members of an organization. This approach reflects the importance of laying down a foundation of knowledge and understanding prior to initiating operational activities in a given location. Even cognitive process models, such as Ulric Neisser's perceptual cycle, describe a psychological process in which "anticipatory schema" prepare the perceiver to detect certain kinds of new information that then drives the modification of a person's understanding.

Data Processing

Perceiving and understanding sociocultural behavior and the sociocultural environment is complex and difficult. Collecting data in the operational domain presents challenges: behavioral and environmental data is frequently difficult and dangerous to collect, access to the populace may be limited or denied, and cultural and language differences act as barriers. The chapter on data processing, by Elson, Dingwall, and Moaddel reviews some of the challenges and addresses two developing approaches for achieving sociocultural understanding in operational domains. The first approach focuses on two research methodologies – content analysis and survey research – that support the understanding of variables such as population values, attitudes, and ideologies. The second centers on burgeoning techniques for processing and understanding the output of mass communication tools such as Twitter. The authors discuss both the challenges of cross-cultural research and promising recent innovations.

Computational Modeling

Humans are social actors who co-create complicated, adaptive systems; models of their orientations, actions, and environments can benefit from advanced methods and mechanisms. This chapter presents a sampling of the models and modeling techniques currently in use or under development that can represent social actors at both the individual and group levels. The chapter focuses on enhancements of various network, cognitive, and game-theoretical algorithms and models. Discussion of each technique addresses the factors a tool-user should consider when identifying the most appropriate technique, including assumptions about actor knowledge, data requirements, the representation of human activity, the level of analysis implied by the model, and how the model adapts to the system/environment.

Visualization

Data visualization exploring the interconnections among social and cultural forces that manifest themselves in a variety of personal interactions is a complex and daunting task. Once sociocultural data have been identified, collected, processed, and used as input for computational models or to typify a snapshot of social interactions, the generated output, be it quantitative or qualitative, benefits from a visual display commensurate with the captured dynamics at play. Without good visualization tools and techniques, translating data into situation awareness and into useful recommendations becomes problematic. Ryan's chapter describes methods for visualizing quantitative and qualitative data, whether to provide organizational insights into the structure of a society or to characterize events that engage a society through its social networks. In addition to the more traditional means of displaying sociocultural data, the chapter examines new techniques for visualizing understanding in multi-dimensional space and the challenges presented by visualization using the next wave of data amalgamation – big data. These techniques afford analysts access to a multiplicity of media made available through technological innovations currently still in the experimental domain.

Training

Achieving operational success depends not only on the ability of *researchers* to collect and process data, model the sociocultural environment, and visualize input and output, but also on the ability of *operational end-users* to gain access to the right data, analyze those data, use the data as input into models, and understand the models' output. As is the case with all new tools and techniques, successful application and use requires training. This chapter, by Behymer, Mateo, McCloskey, and Abbe, describes two categories of training tools – those that focus on interpersonal interaction and those that address group- or population-level dynamics. Training tools that emphasize interpersonal interaction use text, video, or virtual environments to simulate situations and interactions with others, while the tools focusing on group dynamics use multi-media tutorials, real-world imagery, and virtual environments to help end-users develop observational skills that will help them interpret and understand unfamiliar sociocultural contexts.

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1 Sociocultural approaches to understand human interaction: A discussion of new theoretical frameworks, issues, and modern communication technology[1]

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1. Introduction to Sociocultural Understanding

> The sons of Adam are limbs of each other,
> Having been created of one essence.
> When the calamity of time affects one limb
> The other limbs cannot remain at rest.
> If you have no sympathy for the troubles of others,
> You are unworthy to be called by the name of a Human.
> – Sa'adi Shirazi, 13th century

> No man is an island entire of itself; every man is a piece of the continent, a part of the main; if a clod be washed away by the sea, Europe is the less, as well as if a promontory were, as well as any manner of thy friends or of thine own were; any man's death diminishes me, because I am involved in mankind. And therefore never send to know for whom the bell tolls; it tolls for thee.
> –John Donne, 1624

That these luminaries from diverse cultures and times arrived at the same conclusion regarding the psychic unity of mankind may lend credence to the premise that all cultures strive for social harmony, compassion, and peace. This eloquently articulated, idealistic view of humanity, however, cannot be easily reconciled with the persistent misunderstandings arising from cultural diversity and the reality that conflicts not only occur among cultures but that cultures themselves contain conflicting elements. The clashes within and between cultures run contrary to the concept of unitary, caring, and compassionate humankind that Sa'adi and Donne celebrated.

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While sociocultural theories of human interaction abound, this chapter focuses on two basic approaches for gaining sociocultural understanding. The first approach uses a theoretical framework to foster medium-term, a period between 10 and 15 years, sociocultural understanding, while the second employs the new technologies of mass communication to enable rapid understanding of how information, ideas, and propaganda flow through various outlets as well as the manner in which the information flow shapes political actions, including extremism.

The theoretical framework underlying the first approach illustrates how sociopolitical and cultural issues serve as indicators of trends in values and ideological change in the medium-term. In describing this framework, we discuss two research methodologies that support it: content analysis and survey research. Content analysis applies to data collected in real time from social media outlets that reveals people's perceptions of issues and events. It provides quick information for understanding changes in the sentiments, emotions, and attitudes of the subject population in the short run and how such changes are linked to different forms of political action. With regard to survey research, we focus on the challenges of conducting cross-cultural surveys and on innovations in survey techniques that are not yet in widespread use.

Section three in this chapter, Technologies to Promote Near-Term Sociocultural Understanding, focuses on innovative tools that can help researchers gain understanding of sociocultural issues in near-real time. Many of the tools described are currently in development or are used only by select organizations, but should become more broadly available in the near future. We then discuss gaps in the technologies that research should address in the future. We conclude by describing the actions necessary to bring state-of-the-art technologies and methods into operational use.

We must emphasize the importance of understanding culture as an overall framework for viewing the world. The interaction between society and an individual can influence the development of self-schemas through changing expectations regarding self-awareness (i.e., individualist vs. collectivist societies), social judgments (i.e., adhering to group norms), and social behaviors. But just as our own sociocultural perspectives affect our own thoughts, feelings, and behaviors, it can also color how we view other people or groups. Therefore, it is important to recognize how social context and sociocultural perspectives may influence individual or group behavior. In the section of the book covering detection of sociocultural signatures, a chapter on training presents additional discussion of culture as an overall framework.

2. Theoretical Framework for Medium-Term Sociocultural Understanding

2.1. Sociopolitical and Cultural Issues as Indicators of Trends in Values

"Social change" is an umbrella term used to capture such observable aspects of social life as changes in (a) the principles of social organization (e.g., economics and politics, the form of government, or the relationship between religion and politics); (b) religious beliefs and institutions (e.g., the rise of different religious movements, sects, and cults); (c) values, rituals, identity, and life-style (significant changes in people's religiosity, consumption habits, and style of dress); and (d) the arts and literature. The actual process of change, however, is complex, and its probable forms

and content are hard to detect. In some cases, change appears chaotic, exhibiting few discernible patterns; only multifaceted group conflicts, sociopolitical upheavals, violence, and contradictory events are evident. In other cases, by contrast, change lies hidden beneath the veneer of political stability and smooth economic transition. A sudden emergence of revolutionary movements leading to the breakdown of the existing political order and changes in social relations can interrupt a stable and quiet period of economic development. In the first instance, we know that changes are transpiring, but we do not know the direction of these changes and what cultural pattern will predominate. In the second, we expect the emergent cultural pattern to correspond to the observable indicators of economic development and political formation and are surprised when a strong countercurrent surfaces.

We suggest that certain indicators in public opinion and attitudes, as well as in the expression of intellectual leaders and opinion makers, offer reliable measures of the extent of support for existing sociopolitical and cultural orders. These indicators may change in finite ways, and the direction of changes in these indicators provides clues about the possible content and form of social change in a period encompassing less than a generation—the medium run. We also suggest that historically significant issues function as indicators and barometers of change and that the manner in which issues are resolved signifies the direction of changes in some or all aspects of culture. In some cases, the resolutions entail revolutionary change, causing the existing societal model to be abandoned or modified in favor of another. For example, in the years preceding the Iranian Constitutional Revolution (1905–11), the arbitrary power of the monarch became a political issue among intellectual leaders and activists. Cultural change occurred when the revolution substituted a constitutional modality of politics for monarchical absolutism. In the years preceding the Iranian Revolution of 1979, on the other hand, the pro-Western monarchy-centered secular modality, rather than the monarch's authoritarianism, was the predominant point of contention. The revolution resolved it by substituting clerical absolutism for monarchical dictatorship (Moaddel, 1993; 2005).

In other cases, issue resolution takes the form of a rather gradual shift toward, for example, gender equality or gender hierarchy, democracy or authoritarianism, liberal values or religious government, and national/ethnic or religious identity. These changes may then shape the probability distribution of the success of different political groups, movements, or political parties.

The model proposed here parameterizes issue resolution in terms of the variable features in the dynamic context of ideological debates and religious disputes among both intellectual leaders and the public at large, on the one hand, and the role of the state as well as politically powerful groups in this context, on the other. While culture is conceptualized "as a 'tool kit' of symbols, stories, rituals, and world-views" (Swidler, 1986, p. 273), we argue that it hardly constitutes a consistent set of values, norms, rituals, symbols, memories, and institutional principles. Rather, it contains incongruent elements that often clash. In fact, fundamental cultural values derive their meaning from opposition to other cultural values that may exist in the same culture. This means that multiple cultural schemas exist simultaneously in a social environment and can convey contradictory messages about values, goals, and appropriate methods. Given these multiple, potentially conflicting schemas, one cannot claim that any particular culture dictates certain types

of decision making and behavior. Instead, as discussed by Swidler (1986; 2001), cultural models generally provide goals and strategies from which people can choose in making specific decisions. Thus, individuals can follow one set of cultural elements in a particular circumstance and another set of elements in a different circumstance. This is true, because “people, manifestly, care about more than one thing—indeed, are, simultaneously and sincerely attached to values that clash”(Sniderman, 1993, p. 224).

The existence of diverse cultural schemata that shape different, if not conflicting, strategies of action creates the potential for perpetual conflicts in society. This diversity complicates intracultural and intercultural understanding. Nonetheless, sociopolitical stability is ensured when a subset of cultural elements is formalized into a dominant discursive framework, becomes the guiding principles of social interaction, and gains the appearance of permanence and taken-for-granted features of social order. Certain social institutions and watchdogs maintain and protect the dominant discourse, which is ultimately sanctioned by state power.

2.2. Cultural Debates, Religious Disputations, Political Conflict, and Issue Resolution

Cultural change may occur when individuals or groups challenge some or all of the elements of the dominant discourse, these elements are turned into issues, intellectual leaders offer resolutions to the issues, and a significant section of the population, members of powerful groups or social classes, or the ruling elite accept those resolutions. Thus, an important aspect of understanding cultural change entails understanding the actual process involved in resolving issues.

The emergence, debate over, and resolution of issues constitute a non-anonymous and observable process. The process begins when producers of sociopolitical ideas turn such aspects of daily life as people’s social identity, the status of the economy and distribution of economic resources, poverty, social and cultural inequality, arbitrary rule, national security, the perceived status of a nation or community vis-à-vis others, or people’s spiritual needs into topics of debate. What requires explanation is how intellectual leaders offer resolutions to these issues. How, for example, do they resolve issues related to identity and economic difficulties? Definition of identity may be resolved in terms of religion, nationality, ethnicity, or language. Similarly, societies may address economic difficulties in socialist terms at one extreme, or, at the other, by giving tax incentives to the rich in order to promote investment in the country.

The actual resolution of issues may, however, derive directly neither from the nature of these issues nor from the social positions of the individuals involved in the cultural debates. To be sure, social position constrains expression. An intellectual leader from a humble background may be more sympathetic to a socialistic idea than to the idea of competitive capitalism. Nonetheless, that same person living under Soviet totalitarianism might turn into an enthusiast of the free market capitalism. To give another example, people born in Egypt may have only three possibilities for defining their primary identity: Egyptian, Arab, or Muslim/Christian. Nonetheless, it is crucially important to understand how under certain historical circumstances Egyptians define themselves primarily in national territorial terms (i.e., as Egyptians), but under other circumstances in terms of language (i.e., as Arabs) or religion (i.e., as Muslims/Christians).

2.3. Ideological Target as a Key Factor in Issues Resolution

We argue that societies resolve issues within the dynamic context of intellectual debates, religious disputes, and political conflict as each side of the debate structures the sociopolitical expression of the other side. Each side constitutes the target of ideological production for the other side. In a national context, where the key actors are the regime and its opponents, political activists define their collective identity, specify cultural framing, and resolve sociopolitical issues in oppositional relation to the ideology and identity of the state. The latter may be national or foreign, secular or religious. This oppositional context determines whether people define their collective identity in terms of the nation, language, ethnicity, or religion. For example, territorial nationalism in Algeria and Egypt emerged in an oppositional relation to foreign occupation (the French and British, respectively), and anti-clerical secularism and constitutionalism in Iran in the late nineteenth and early twentieth centuries emerged in oppositional relation to *ulama* religious obstructionism and monarchical absolutism (Moaddel, 2005). Some discourses, such as Islamic modernism, fundamentalism, and various forms of secularism—liberal nationalism or authoritarian nationalism—have formed comprehensive cultural movements. Other discourses, such as Arabism and pan-Arab nationalism, have focused on language as the organizing principle of cultural movements.

2.4. Methodological Tools for Collecting Cultural or Attitudinal Data

In collecting sociocultural data, researchers can use various methodological tools, including comparative-historical investigations, participant and non-participant observation in the field, experiments, and discourse analysis. Here, we focus on two basic tools that have proven useful in collecting cultural or attitudinal data in order to understand and predict change. One centers on analyzing the content of the expressions of intellectual leaders, opinion makers, and bloggers. An analysis of these expressions through time generates useful information for reconstructing intellectual trends in a society and predicting the form of future political and cultural movements. For example, the discourse of pan-Arab nationalism that inspired the military coups in Egypt, Iraq, Libya, and Syria in the 1950s through the 1960s originated in the 1920s. In the same way, the discourse of radical Islamism most prevalent today was formulated in the 1950s and 1960s.

The other method applies survey research to assess the attitudes and value orientations of the ordinary public. Surveys are effective ways to generate scientific knowledge about the role of culture in human lives and the causes and consequences of mass belief systems. Longitudinal and panel survey data provide useful information for understanding trends in values in the population of interest. The following subsections outline key topics related to conducting successful surveys.

2.4.1 Challenges in cross-cultural survey research

The quality of survey data is a function of the extent to which the researcher formulates all three components of survey research correctly: the questionnaire, sampling, and interviews. These criteria are particularly important in the context of cross-cultural survey research. We describe below several methods used to facilitate the conduct of cross-cultural surveys in light of the challenges that may confound the findings and undermine the validity of scientific generalization.

Questionnaire Development. The items in the questionnaire must be clearly linked to, and constitute valid and reliable measures of, the theoretical constructs that drive empirical research. To this end, researchers must consider several aspects of questionnaire development, including translation issues, cultural sensitivity, and item organization and context within the instrument itself.

When questionnaires originally written in English are used to measure attitudes and value orientations across multiple non-English speaking populations, researchers must ensure that the translation does not lose or distort meanings. One standard procedure to reduce the influence of linguistic differences entails (a) translation of the questionnaire from English to the vernacular by a competent translator, (b) back-translation of the questionnaire from the vernacular to English by someone who has not seen the original English version, and (c) a systematic comparison between the two English versions. Another approach, which could either complement or substitute the standard procedure to reduce cost, is to poll some non-English respondents regarding their understanding of the questions during the pilot testing of the questionnaire. If responses are consistent with the intention of the question, then the question can be considered a valid measure of the construct.

Scholarly flexibility and non-ethnocentrism are also important considerations in questionnaire design. For example, in some cases the version of the questionnaire in the vernacular, although different from the English version, more effectively taps into the respondents' sentiment and intentions. In such a case, the researcher must modify the English version to conform to the vernacular version. For example, in a recent cross-cultural survey of populations from relatively diverse countries such as Egypt, Iraq, Lebanon, and Saudi Arabia, the initial questionnaire included the question: "Given the opportunity, how often do you think that men will try to take sexual advantage of women: always, sometimes, rarely, or never?" Both the Egyptians and Saudis argued that the wording in Arabic referring to sexuality would be too sensitive in their home countries, which led to the revised wording: "Given the opportunity, how often do you think that men will harass women?" The revised question uses less inflammatory language while still accessing the original intention of the question. Additionally, there may be Western biases in the types of values addressed in survey questionnaires. For example, questions on religious tolerance or gender relations may lead to a negative image of Muslim-majority countries, as these countries appear less tolerant of religions other than their own or more supportive of gender inequality and hierarchization.

Studies have shown that how questions are worded and framed, including the choice and order of response categories, can have significant effects on the responses (McColl, et al., 2005). Furthermore, while non-locatable participants and refusals may affect data quality (Braver & Bay, 1992), other kinds of self-selection biases that result from the respondents' cultural outlooks may be more subtle and their effects harder to assess. For example, the connection between watching satellite TV and religious attitudes may become complicated if people with conservative outlooks decided against installing satellite TV in their homes. Finally, over-reporting socially desirable and under-reporting undesirable behaviors/attitudes is another serious problem that may have considerable impact on the quality of the data (Cahalan, 1968; Gordon, 1987; Hyman, 1944; Parry

& Crossely, 1950). In Muslim-majority countries, for example, the social desirability bias emerges most clearly in such questions as those that solicit respondents' attitudes toward homosexuality and prostitution. While anecdotal evidence indicates the presence and even tolerance of (male) homosexuality and prostitution in these countries, at least ninety percent of respondents in surveys of the publics from these countries said that such acts are never justifiable, which would probably indicate social undesirability bias. Furthermore, asking people in these countries whether they had ever practiced homosexuality would almost certainly anger the respondents, terminating the interview. Questionnaire design must take into account contextual effects and desirability biases such as those reported in the examples above in order to produce reliable and valid data.

Sampling. Samples of country populations must be nationally representative, with all respondents having a known probability of selection. In many non-Western societies, the formulation of an effective sampling frame presents a serious challenge, particularly in the absence of recent census data. Researchers must assess how any changes in the sampling procedures as a result of unforeseen factors might affect the representativeness of the final sample used in the study. These may include where the non-availability or inaccessibility of detailed census data requires using alternative spatial sampling or using the random-walk procedure, or where the outbreak of a war or political violence may make certain areas inaccessible to the interviewers or causes mass migration. When designing samples for use in cross-cultural survey research, researchers must also consider comparability of the samples across countries and across time within countries.

Interviewers. Interviewers' skill level, their understanding of the questions, and honesty will make or break the validity of the entire process of data collection. Interviewers must be well trained and well paid, and the field supervisor must review their work. In the context of cross-cultural survey research, comparable interviewer training is also crucial.

2.5. Innovation in Survey Methods: Understanding the Causes of Popular Attitudes

Although surveys have made it possible to gain sociocultural understanding, traditional surveys have been limited in that they do not allow analysts to understand the causes of attitudes that respondents hold. Only experimental methods can pinpoint the drivers of human behavior or the reasons why people hold the attitudes they hold.

Numerous texts, such as Shadish, Cook, and Campbell (2002), contain in-depth discussions of experimental methods. In essence, an experiment is a study in which the researcher deliberately introduces (or "causes") an intervention in order to observe its effects. As an example, a researcher might have a theory regarding the aspect of a message that makes it persuasive in a population of interest-for the purposes of this discussion, some characteristic of the person delivering the message, such as his/her age. To test this theory, the researcher might conduct a randomized experiment. For this experiment, the researcher must first recruit a sample of participants who, ideally, represent the population of interest (e.g., intelligence analysts). The researcher then might use a coin toss or random number generator to assign each participant to one of two conditions. In the first condition, participants view a message ascribed to an older person, while in the second condition participants view exactly the same message, but are told that a younger person delivered

it. By randomly assigning participants to view either the message delivered by an older person or a younger one, the researcher can ensure that both groups are reasonably similar to each other. Therefore, if one group finds the message more persuasive than the other group does, this difference is probably due to the factor being tested (i.e., age of the source delivering the message) rather than to any pre-existing differences between the groups. In this way, researchers can establish a causal link between some aspect of a message (e.g., age of the source) and the persuasive power of that message.

Although experiments have traditionally been conducted in academic labs, technology now enables researchers to embed experimental methods within surveys, thus combining the strengths of each method. Namely, it is now possible to explore causal relationships in human behavior via a survey, enabling researchers to "work at scale" by examining a large and representative sample of an entire population. A population-based experiment uses survey sampling methods to obtain a set of participants representing a target population of interest for a particular theory—whether that population is a country, a state, an ethnic group, or some other group. In such experiments, the researcher randomly assigns participants to conditions, and inserts interventions as in any other experiment. New technologies, such as Computer-Assisted Telephone Interviewing (CATI) and the internet itself, have made it easier to randomly assign participants to conditions without asking them to come to a particular place for initial screening. For this reason, researchers wanting to discover a causal relationship that generalizes beyond a narrow pool of participants are well advised to use population-based survey experiments.

Although these experiments are administered to representative samples of the target population of interest, they need not target nationally representative population samples, and often have not done so. The population of interest might be members of a particular ethnic group, parents of children under the age of 18, people who watch television news, or some other subset of the national population. This ability to tailor the sample constitutes the great advantage of population-based survey experiments: researchers can test theories on samples representative of the populations to which the theories are said to apply.

3. Technologies to Promote Near-Term Sociocultural Understanding

Up to this point, we have discussed a theoretical framework and methodological approaches for gaining sociocultural understanding that have long traditions in the behavioral sciences—and are described in commensurately broad research literatures. However, with the advent of new forms of communication via the internet (e.g., social media), researchers have developed new technologies for collecting the voluminous data generated. In particular, social media outlets such as Twitter, Facebook, YouTube, blogs, chat rooms, and others require a new set of methods and technological prototypes to conduct analysis—particularly when trying to gain sociocultural understanding in the short term. We now turn to these newer methods and technologies, in the hope of introducing the reader to technologies that are ready for use but perhaps not yet widely known. Because these technologies are at different stages of readiness for use, we have grouped them according to whether they are deployed, whether they are in prototype form but not deployed, or whether they are in a research phase.

Deployed Technologies

3.1. Topsy

Topsy analyzes tweets and web pages gathered from millions of websites, blogs, and social media services. The platform supports all languages, and combines a search engine and analytic tools that index, analyze, and rank content and trends. Topsy's pipeline architecture currently processes over 400 million posts every day from multiple data sources, generating ranked and scored results within a few minutes. Topsy currently operates the world's largest global index of Twitter data and gives access to conversations in near-real time as well as to an archive going back several years. Customers that include U.S. Government agencies, global marketing firms, and large online publishers use Topsy to monitor activity by keyword, domain, and geographic areas and analyze content by media type (links, photos, videos), author, and sentiment. In addition, Topsy's indexing and live-ranking technologies process content from social networks, helping users to determine the relative resonance of various topics and to identify "tipping points" in message exposure. Users can also develop predictive trending metrics and conduct historical analysis to correlate social media activity with real-world events. This analysis provides the ability to view historical activity and to compare activity levels for related topics over long periods of time. The platform supports any language regardless of character set.

3.2. InTTENSITY

InTTENSITY has created a suite of tools to enable sociocultural understanding (inTTENSITY, 2013). One of them, the Social Media Command Center (SMCC), combines a social media harvesting service with extraction and categorization engines; the combination of these provides an analytical capability using a cloud-based approach. The SMCC examines 75 million social media sources, including Twitter, Facebook, and a variety of public blogs and pages. It specifically looks for spikes in social media volume of any sort compared to a normal distribution (as calculated and adjusted periodically by a baselining activity). For example, if normal Twitter frequency for a given day and hour is approximately 1,000 tweets per second and the SMCC detects a spike up to 3,000 that persists for a sustained period within that timeframe, the system identifies and collects statistics about that spike. In this way, researchers can use the SMCC to detect and gather information on any high-impact events, including mob violence, civil disturbances, natural disasters, or any other event where people use their mobile devices to "check in."

SMCC can filter data by geography and keywords, enabling users to focus on an event within a specific area. The system works with unstructured text data and enables users to manipulate the processed data based on specific categories. Furthermore, the classification technology recognizes and displays relationships between data points and divides the results into contextual groups. Its clustering functionality classifies unstructured information into thematic groups, identifies the major topics in documents, and recommends structures for classification.

InTTENSITY has also built the InTTENSITY Analyze tool, which transforms text in social media, emails, surveys, and other sources into insights regarding sentiments and trends. Specifically, InTTENSITY allows users to automatically discover topics of conversation in social media, emails,

surveys, and other sources; analyze coverage in social media; profile social media user behavior and preferences; and measure the effectiveness of information campaigns.

3.3. Worldwide Integrated Crisis Early Warning System (W-ICEWS)

W-ICEWS, developed by Lockheed Martin with funding by the Department of Defense (DoD), consists of technologies that monitor, assess, and forecast the occurrence and evolution of instability events throughout the world (Lockheed Martin, 2013). W-ICEWS provides situation awareness that is designed to help produce planning products, crisis action planning, and post-execution analysis. The system comprises four components that together perform near-real time data extraction and analysis from news reports and information generated by the government Open Source Center (OSC).

W-ICEWS Data Management (iDATA) provisions W-ICEWS models in near-real time with data from over 6,000 international, regional, national, and local news sources (Lockheed Martin, 2013). The software has processed more than 30 million news stories in English, Spanish, and Portuguese from the past 13 years to extract "who, did-what, to-who, when, where." iDATA uses deep (BBN Serif) and shallow (JabariNLP) parsing technologies to produce over 19 million unique geolocated events with an accuracy of greater than 80 percent. iDATA draws over 300 different types of coded events from the CAMEO (Conflict and Mediation Event Observations) taxonomy, with each event type having an observer-neutral intensity (Goldstein) score that represents how hostile or how cooperative the event is. The actors (country, sector, organization, individual) involved in events come from dictionaries of over 50,000 named and time-indexed entities as well as over 700 generic agents (e.g., police, government official, protestor). The iDATA repository also contains data from 30 different sources that contain primarily quantitative data on over 175 different countries. Because many countries do not publish reliable information (e.g., the gross domestic product of Afghanistan), iDATA uses a type of data imputation known as the hybrid copula method to impute missing data records. A copula is a joint cumulative distribution function that captures the dependence among a set of random variables (Hollenbach et al., 2013). It is a function that binds together two or more univariate marginal distributions of known form to produce a new joint distribution (Trivedi & Zimmer, 2005).

W-ICEWS Trending, Recognition, and Assessment of Current Events (iTRACE) aids situational understanding through analysis and visualization of event history trends and patterns generated by iDATA (Lockheed Martin, 2013). It gives users capabilities to generate time series, map-based views, trends, relationships, matrices, and other visualizations, with drill-down to underlying stories. iTRACE provides an automated capability to monitor political activity around the globe by automatically converting news reports into structured indices that reflect the character and intensity of interactions among key leaders, organizations, and countries—who is doing what to whom, when, where, and how around the world. Users from various military, government, and intelligence communities use iTRACE to create analytical products. iTRACE was transitioned into U.S. Strategic Command's Integrated Strategic Planning and Analysis Network (ISPAN) framework in the spring of 2012 on both the Secret Internet Protocol Router Network (SIPRNet) and the Joint Worldwide Intelligence Communication System (JWICS). This capability, coupled with other W-

ICEWS components, is available on U.S. Southern Command's unclassified W-ICEWS servers for test and evaluation.

W-ICEWS Forecasting (iCAST) provides the capability to forecast instability events around the globe, using a mixed methods modeling approach to forecast instability (Lockheed Martin, 2013) iCAST combines forecasts from heterogeneous statistical and agent-based models to generate an aggregate forecast with accuracy greater than 90 percent (Ibid). Users can drill down into the underlying model variables and data to gain detail on the forecasts and can experiment with the effects of changes on the model indicators in a "what-if" scenario.

Finally, W-ICEWS Sentiment Analysis (iSENT) measures attitudes and perception about issues, people, and events through sentiment analysis from blogs, tweets, and Facebook (Lockheed Martin, 2013). It also shows sentiment propagation across the internet and identifies key sites and people in shaping opinion dynamics. Open source digital content generated by recent events, such as the Arab Spring and London riots, creates a valuable source of information. Using such information, iSENT can give intelligence analysts the tools to understand emerging regional trends and sentiment, predict threats from groups and individuals or find the proverbial "needle in a haystack." Its analysis algorithms are designed to distinguish between useful information and noise in a rapidly changing content. iSENT developers have conducted experiments with operational organizations, transitioned the capabilities for operational use by intelligence analysts and desk officers, and integrated with other W-ICEWS components and the ISPAN program of record.

3.4. Marine Corps Civil Information Management System (MARCIMS)

U.S. Military Civil Affairs (CA) teams currently lack the ability to efficiently share and analyze critical information and experiences they collect during engagements with the civilian environment. MARCIMS aids effective Civil-Military Operations (CMO) by providing knowledge of the battlespace through mobile computing technologies, semantic information and knowledge management, and Web-based geospatial decision support capabilities. MARCIMS's technical approach begins with data collection using apps on iOS and Android smartphones with configurable forms and real-time submission of data to a central repository through local cellular or wireless networks. In addition, MARCIMS displays field-collected CIM data in context with basemaps and overlays of relevant imagery and geo-data. Users can access geospatial analysis and statistical reasoning tools via standard Web service protocols. Finally, MARCIMS enables users to manage and analyze relationships between field and reference datasets in a Semantic Wiki interface.

Prototype Technologies

3.5. TweetTracker

Arizona State University professor Huan Liu and his colleagues designed the TweetTracker to assist users involved in Humanitarian Aid and Disaster Recovery and other complex operations to identify topics of current concern to crowds (Goolsby & Carley, 2013). Liu collected over 200 million disaster- and crisis-related tweets. U.S. European Command has already instantiated the TweetTracker in its Social Media Dashboard.

TweetTracker helps users to spot rumor and viral information by leveraging the capabilities of news organizations and other sources that collect, sort, vet, and distribute information. For example, TweetTracker can help a user find the top retweeted URL, breaking news, influential people, human sensors on the ground providing on-the-scene reporting, and other items of particular interest to Military Information Support and/to Operations (MISO).

In addition, TweetTracker capitalizes on the fact that many Twitter users gather and generate data professionally and semi-professionally (i.e., newscasters, bloggers, etc.). These users collect vast amounts of detail gleaned from their own informants, discover important events, and distribute vetted information about events. TweetTracker enables users to monitor, leverage, and exploit such broadcast information, and discover capable crowd networks and to analyze information pathways and content for actionable intelligence.

Along with the capabilities described above, TweetTracker allows users to find illustrative tweets, a view of the overall network, the most retweeted actors, the hashtag network, and the most critical hashtags (i.e., those that co-occur most frequently with other hashtags). At present, users can compare the numbers of tweets marked with different hashtags. Furthermore, users can separate English from non-English tweets. Finally, users can display trends in news articles and in Twitter items on the same topic, conduct multi-country comparisons of the number of tweets per hour, and track the number of tweets mentioning a topic across time.

3.6. Social Radar

The MITRE Corporation's Social Radar prototype provides population-centric signal-detection capabilities that can yield early insight into diverse events such as unrest in Africa, natural disasters in East Asia, or disease outbreaks. The Social Radar capabilities enable users to track perceptions, attitudes, beliefs, and behaviors of a population as expressed via Twitter, blogs, and news. Social Radar offers an indications and warning capability, in which users launch mini-applications or "widgets" that may work independently in a modular fashion or may communicate with each other. Within the Social Radar prototype, researchers can utilize two applications to understand the sentiments or emotions expressed regarding a topic.

The Sentimedir prototype (Day, Boiney, Ubaldino, & Brown, 2012) supports detection and tracking of trends in sentiment as expressed in news articles and comparable texts. Users can quantify and visualize the direction and rate of change in sentiment, while controlling for various features of the text such as topic, source, geography, persons named, and more. Users can design highly tailored queries and save them for efficient reuse, updating, and collaborative sharing. They can also drill down to individual sentences or documents, to view annotations of sentiment in context. The technical core of Sentimedir is a set of statistical sequence models that use semantic and lexical features of individual sentences to infer three elements of sentiment expression: (a) *opinion holder*—the person, organization, or metonymous mention of a geopolitical entity, (b) *sentiment expression(s)* —specific terms or phrases, in context, that convey the negative or positive polarity of an opinion holder's sentiment, and (c) *sentiment target*— the concept or entity on which the opinion holder's expression of sentiment is focused.

The MoodMiner tool suite comprises a set of behavioral scientific analytic methods and an automated prototype for understanding trends in emotional expressions. At present, MoodMiner has been applied only to Twitter, but will be extended to other social media. This tool enables users to query tweets and plot trends in emotion levels in real time—both generalized emotions and expressions regarding specific targets. The emotion categories used within the prototype are drawn from social psychological research that examined linkages between the words people use in written texts and the psychological states they experience. Specifically, the research used to develop the Linguistic Inquiry and Word Count (LIWC) framework within social psychology also informed the development of the prototype.

In addition to monitoring the emotions and sentiments expressed toward a topic over time, users may wish to understand—at a glance—the most relevant topics being discussed in a set of text data or to pinpoint the demographic characteristics of those posting tweets. Alternately, users may wish to uncover deception in the tweets. Each of these analyses can be conducted within Social Radar.

Users can draw on Comment Filter (CoFi) to perform exploratory analysis of text data sets in any language by using NLP techniques to group similar comments and to prioritize messages such that the most relevant items can be identified quickly (Doran, Zarrella, & Henderson, 2012). CoFi automatically discovers topics, grouping similar comments, sorting comments by relevance, and providing drill-down and timeline-based visualization. It works with other analytics that detect elevated levels of information sharing behavior, such as retweets, and can partition social media comments by language and country of origin to provide a more targeted perspective to the analyst interested in drilling down to search messages for actionable content.

Users who wish to understand the demographic characteristics of those posting to Twitter can draw on Author DNA to characterize unknown authors along several attributes, including gender, age, and location. Burger, Henderson, Kim, & Zarrella (2011) cast the problem as one of text classification, viewing each author as a set of identifying features derived from the content and metadata associated with all of the author's postings. These features include the sets of words and characters used in the tweet text itself, as well as the author's self-description, screen name, time zone, posting times, text length, emoticons, capitalization and punctuation density, and numerous other attributes associated with a user's social activity. Burger, Henderson, Kim, & Zarrella, (2011) built a statistical profile over these units, and compared it to known samples by measuring the similarity of these distributions. This approach is agnostic about language or writing system, making it applicable to many organizations' problem spaces.

Author DNA has so far focused on machine learning algorithms that can be trained quickly on very large amounts of training data. Henderson, Zarrella, Pfeifer, and Burger (2013) have labeled more than 20 billion tweets with a country of origin, and have performed a series of validation experiments using a sample of Twitter data built over the course of four years. They used blog profile metadata and tweet geo-tags to measure the correctness of their predictions, with results suggesting that the algorithms are roughly 92% accurate at associating a Twitterer with a country.

As a practical matter, Twitterers who produce more tweets are more likely to be tagged more accurately, so the approach is well suited for discovering highly active Twitterers from any region of the globe.

Users who wish to detect deception or covert activity in social media can turn to the Pinocchio widget, which searches for covert information campaigns operated by hidden networks of social media accounts. "Puppet" accounts such as these are often used to conduct fake grass-roots campaigns to distort the online conversation or magnify perceived influence. Pinocchio searches for a constantly-updated list of rare watermarks that are potentially unique to the style or substance of an individual user's messages, such as unusual phrases, hashtags, or URLs. When the widget discovers multiple accounts that repeatedly share the same rare watermarks, it flags those users as potentially suspicious. When those flags start appearing between all members in a much larger set of accounts, at statistically unusual rates, Pinocchio builds up a high-level picture of who is colluding to deceive honest users of social media.

Research Phase Technologies

3.7. Program on Social Media in Strategic Communication (SMISC)

According to the website of the Defense Advanced Research Projects Agency (DARPA, 2013), DARPA launched the Social Media in Strategic Communication (SMISC) program to develop tools that would help human operators to counter misinformation or deception campaigns. The program focuses its research on linguistic cues, patterns of information flow, and detection of sentiment or opinion in information generated and spread through social media. Researchers will also attempt to track ideas and concepts to analyze patterns and cultural narratives. If successful, they should be able to model emergent communities and analyze narratives and their participants, as well as characterize generation of automated content, such as by bots, in social media and crowd sourcing.

SMISC researchers are creating an environment where large amounts of data are collected, with experiments performed in support of development and testing. One example of such an environment might be a closed social media network of 2,000 to 5,000 people who agree to conduct social media-based activities in this network and to participate in required data collection and experiments. This network might be formed within a single organization, or span several. Another example might be a role-player game in which use of social media is central and players have again agreed to participate in data collection and experiments.

4. Gaps in Science and Technology

Although research has made great strides in developing technologies for ingesting and analyzing social media data, certain gaps remain. One technological gap limits the ability to differentiate between people’s “public” versus “private” selves from social media data. In addition, given that several of the technologies discussed in this chapter include programs for tracking linguistic patterns in text data, we note two gaps in the area of linguistics and culture. A fourth gap concerns the use of virtual reality games (or lack thereof) in research designed to gain sociocultural understanding. Finally, a fifth gap lies in the scientific tradecraft available for utilizing the diverse

methods of data collection available (e.g., survey research, social media analysis, and others). Specifically, a question arises as to whether insight gained from social media is analogous to, or comparable with, insight gained from surveys, content analysis, focus groups, Mechanical Turk studies, or other forms of data collection. This question is central to determining whether a user can obtain "ground truth" when utilizing any one of these forms of data collection in isolation. We will address each of these gaps in turn.

4.1. Detecting Public versus Private Selves

As the internet becomes ever more popular worldwide, people increasingly encounter "alternate" social environments and, therefore, opportunities to experience different self-schemas. Although people seek to maintain a consistent view of themselves, the social environment can elicit alternate behaviors and expressions depending on whether it triggers their "public selves" or "private selves." An individual's private self engages in thoughts, feelings, and ideas that form his/her self-schema. The public self, however, is the identity revealed to others, and can be context specific. Oftentimes, the person attempts to conceal the private self, while the public self includes the actions that others can see and acknowledge. Both personas can affect behavior. For example, people may follow social norms at work or in certain social contexts; if they do not, they risk being ostracized by their group. In addition to the physical problems that result from being rejected by a group, ostracism can lead to adverse psychological effects, including on one's overall sense of social well-being (Williams, 2001).

Virtual environments, however, make it difficult to decipher whether an individual is displaying her/his public self or private self. Thus, anyone wanting to tap underlying beliefs would need technology that can distinguish when people are displaying public selves versus private selves. Such technology does not exist at present.

4.2. Psycholinguistics within Foreign Languages

Several of the automated technologies discussed in this chapter track linguistic patterns in text data—whether these patterns consist of the frequencies of words or of phrase structures (such as subject-verb-object "triples"). Although considerable basic research in the English language has linked the usage of specific words with the emotional/cognitive states that people are experiencing (Tausczik & Pennebaker, 2010), very little such research has focused on non-Western languages and cultures. Thus, it is not always straightforward to interpret the linguistic patterns spotted in languages other than English or what these patterns signify regarding people's psychological states. Considerable cross-cultural research will be needed to fill this gap in scientific understanding.

4.3. Tracking Linguistic Patterns in Foreign Languages

Another set of challenges arises because the "languages of the internet" are often combinations of different languages thrown together. For example, Twitter users in the Arab world often combine an Arabic dialect with English (to form what is known as "Arabeezy") and even throw in Twitter slang and emoticons. The combination of such diverse languages as Arabic and English alone poses a formidable gap that yet-to-be-invented technologies may someday address.

As languages, in and of themselves, have evolved through the centuries, the “internet languages” also evolve—quite possibly at a faster rate. Therefore, any technology used to process language must account for the constantly shifting linguistic patterns of the internet. Whether this requires a “human-in-the-loop” to monitor new language patterns or whether research will produce an automated way of detecting new patterns, anyone wishing to analyze social media communication in the long term will have to grapple with “constant change” on the internet.

4.4. Virtual Reality Games for Gaining Sociocultural Understanding

Virtual reality simulations are available for training purposes, e.g., to help troops gain sociocultural understanding before deploying overseas, yet few virtual reality games exist for gaining sociocultural understanding. Such games could be designed and implemented in the context of internet experiments (e.g., using the experimental methodology described above). In this kind of experiment, researchers could examine the decisions that participants make during a game and the thoughts they might communicate for clues as to their sociocultural perspectives. Such games have the advantage of being dynamic and engaging, as well as representing a consistent and systematic mechanism for data collection, since they do not depend on a human telephone interviewer to speak exactly the same way in every interview. For a full discussion of the training tools available for gaining sociocultural understanding, see the Training chapter in the Understand section of this book.

4.5. Conducting Multi-Method Analysis

More than ever before, operational end-users have a choice of data collection methods and analytical processes for gaining sociocultural understanding. These methods include those described in this chapter as well as focus groups, in-depth interviews, on-the-ground observations, and many others. At present, however, few studies have attempted to compare results across different methods—especially when it comes to examining non-Western cultures. A few studies have compared social media results with surveys when it comes to American domestic issues (Mitchell & Hitlin, 2013; O’Connor, Balasubramanyan, Routledge, & Smith, 2010).

This indicates a need for systematic research to understand the factors that may cause different methodologies to converge on the same findings or to diverge—especially with regard to foreign populations. For example, if a social media analysis and a survey project within one culture produce identical results, this “multi-method convergence” suggests that the results are true. However, if the findings diverge, where does “ground truth” lie? At present, little conventional wisdom points the user toward a process for making sense of diverging results. In one culture, people may be afraid to speak the truth in a telephone survey, because they fear being wiretapped, but will readily state their opinions on the internet. However, in cultures that are more open, different methods may yield more convergent findings. In yet another scenario, surveys might tend to reach one demographic group, while social media analyses may cover a different demographic. Again, this pattern of demographic coverage may hold true in some cultures but not in others.

Ultimately, research comparing results across different data formats can clarify how to interpret the results of one type of study. It can also suggest whether or not it would be adequate to conduct only one or another type of study in a given culture, or whether it is more effective to conduct

multiple types of studies. Such research can ultimately contribute toward an analytic tradecraft and best practices for interpreting the results of different types of studies.

5. Transition to Operational End-Users

Although numerous methods and tools now exist for analyzing social media data, developers must meet a series of challenges to transition these tools effectively to operational environments (Allen, unpublished manuscript). For example, a new technology may have unforeseen second-order impacts on business processes and capabilities. To understand the effects on an analytic business process, potential users must outline the business process functions at the most basic level and then postulate specific ramifications ahead of time.

As one example, a new technology provided to intelligence analysts might improve the efficiency of gathering data from intelligence sources. This, in turn, would simplify and speed up the overall super-task of gathering intelligence from multiple sources, permitting analysts to go beyond "Source A" alone to other sources. However, collecting intelligence from any source comprises a set of smaller implicit tasks, such as "understand the data type," "understand the context in which the data was produced," "understand the technical limitations of the collector," and "judge the relevance of the data source to the question." If the analyst was already familiar with Source A, each of these sub-tasks was encapsulated in the super-task. By collapsing several iterations of the super-task (i.e., "Gather from Source B, …C, …" etc.), the new technology exposes the finer-grained tasks, because the analyst is less familiar with the new sources. As a result, while the new technology may consolidate the data-gathering tasks, it extends the processing for validity and relevance enormously—an unintended consequence (Allen, 2007).

Another set of challenges to effective transition of technologies lies in the skill sets that analysts need in order to utilize new technologies effectively. Potential users should carefully consider whether the technology requires advanced disciplinary or specialized training (such as a Master's or PhD in a particular discipline) in order to understand or use it. If the technology makes use of behavioral principles or mathematical processes, for example, agencies may need either to ensure that someone trained in the relevant disciplines is on staff to help analysts navigate the technology, or to provide elaborate training, manuals, and ongoing support as analysts learn the underlying principles for using the technology appropriately.

As one example, analysts must understand the nuances and limitations of particular data types in order to synthesize multiple data sources effectively, especially because most analysts "grow up" within a particular intelligence discipline (Allen, 2007). Developing an analytic strategy across different types of data without having familiarity with all of them, as occurs when huge repositories become available, adds substantially to an analyst's tasks. Furthermore, as described above, altering business processes to incorporate such "new" tasks has a significant impact upon timing, planning, and production processes.

Furthermore, analysts must understand how to develop query strategies in order to pull the data sets they need from the voluminous amounts of data available (Allen, 2007). To date, the typical

analyst is not well versed in more than Boolean or frequency-based querying. Development of query strategies appropriate to the amount and type of data, the particular problem set, and the technical requirements of the storage solution requires better understanding and manipulation of semantic, statistical, and conceptual clustering strategies. To this point, tool developers have made significant strides on developing novel exploitation algorithms, but bridging the gap to the user has been difficult.

The final challenge relates to analysts' overall comfort level with using technology in general, and in particular, with going beyond Microsoft Office. Analysts might require careful training in the use of any new technology, or may need to rely on excellent "cultural brokers" to facilitate the use of that technology. Ultimately, the adoption of new technologies requires adjustments to the new tools, techniques, and processes. Challenges concerning the skill levels of analysts may be especially difficult to address, because they involve changing *people* as opposed to systems or processes.

Separate barriers to effective technology transition lie in the dissemination processes currently used by government agencies. For example, data-sharing agreements made at one agency may incorporate some limitations regarding the types of users allowed to receive the data. This situation creates problems for analysts working in one unit but supporting a Joint or Coalition activity. Furthermore, some regulations stipulate that data can only be retained for a specified length of time, causing problems when performing tasks that require historical data. Similar challenges arise when data sets may be available to answer a question but are not available for review by another organization. For example, an analyst within one unit might solve an analytic problem, but cannot release the relevant detail to the supported unit because of the nature of the information used.

6. Summary

In this chapter, we provided an overview of theoretical frameworks and technologies that researchers can use to gain sociocultural understanding. Although these frameworks and technologies are rigorous, they are not yet widely used in operational contexts. We outlined technologies on the horizon for gaining sociocultural understanding in the medium term and for conducting rapid analysis of large volumes of data for near real-time understanding. This latter mission brings with it the challenge of converting massive amounts of data into tractable units for analysis. Although the technologies available do an impressive job of exactly that, we highlighted gaps in these technologies and in the science of sociocultural behavior sensemaking underlying them. We also highlighted some possible shortcomings that may limit attempts to transition technologies into operational contexts. We hope that the reader will come away with a greater understanding of the avenues available for sociocultural analysis as well as a realistic understanding of the challenges involved in pursuing these avenues.

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2 Modeling cognitions, networks, strategic games, and ecologies[1]

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1. Introduction

Accurate knowledge of human behavior is necessary to deal with many strategic and tactical issues, but attaining such knowledge is difficult. Individuals are complex, self-reflective, and adaptive. Thus, a strategy that succeeds at one time may fail at another. Moreover, group behavior is not simply individual behavior scaled up; lessons learned at the individual level may not apply to a group and vice versa. In short, humans act and interact in complicated systems, and complex models are often necessary to describe them.

This chapter surveys some of the techniques that comprise the current state of the art in modeling human behavior at both the individual and group levels. The discussion is not exhaustive, as much work is being done in this area, but it provides a brief overview of some of the most promising methods currently in development. Specifically, we focus on various types of network-based models, cognitive models, and game-theoretical approaches. Network analysis constitutes an important and growing area of study and is vital in helping U.S. forces to confront decentralized opposition groups. Cognitive models have become essential due to the rise of self-starter terror cells, which plan and execute attacks with minimal or no coordination or resources from a central organization. Finally, game-theoretic approaches apply broadly to understanding equilibrium conditions across a wide range of levels of analysis, while promulgame theory concentrates on how game types interact to produce outcomes. To conserve space we have omitted other useful topics, such as agent-based simulation models, system dynamic models, and uncertainty analysis; these are covered elsewhere in this volume.

Computational models of human behavior differ in (a) the kinds of assumptions made about actors' knowledge; (b) the type of data required; (c) the representation of human activity; (d) the level of analysis; and (e) how adaptation is treated, if at all. We need a firm grasp of each of these factors to select an appropriate model and use it correctly.

Assumptions. All models impose some type of assumptions on the data, but those assumptions can differ markedly. For example, some models assume that individuals have perfect knowledge about

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other group members, while other models assume limited knowledge. Empirical reality frequently violates some of the assumptions underlying a model, so users must assess whether the violations are serious enough to make the model unreliable.

Data Requirements. Models vary in the amount, and type, of data that they require as well as in their potential outputs. Some models require only very high-level demographic information, but produce high-level abstractions. Other models require detailed information on the characteristics and relationships of each modeled actor, but produce reliable estimates of individual attitudes and behaviors (e.g., technology adoption). Thus, both the outputs desired and the type and amount of data available drive model selection. However, there are no free lunches: the amount of data used to feed a model correlates at least roughly with the detail and accuracy of the model's output. This does not mean that accurate data always yields an accurate model, but only that it is difficult or impossible for a model to achieve a higher level of precision than is inherent in its inputs. Similarly, the data must accurately represent the process that analysts hope to explain. Biased or incomplete data will produce biased or incomplete results even when analyzed using the best available model.

Representation of Human Activity Change. Human activity has structure, but models differ in how they represent this structure. Some models assume that human relationships are relatively fixed, while others allow relationships to be born, mature, and finally die. The appropriate representation depends on the application; fixed relationships may be reasonable when modeling short spans of time, but not long spans of time.

Levels of Analysis. Models can be applied to levels of analysis that range from individuals, to small groups, to organizations, nations, and even alliances. Analysts should select models in part on the basis of the fit between the levels of analysis envisioned by the model and the particular entities studied. In many cases the same model may be appropriate for multiple levels of analysis, but the implications of model output can change in both obvious and subtle ways across these levels.

Adaptation. Humans are self-reflective entities, capable of understanding their surroundings and reacting to them. In other words, individuals or groups may recognize an intervention as an intervention and adjust their behavior or thinking in response. Computational models can represent these dynamics, but such modeling must be an ongoing process. Either a model of a social system should have reflexive capabilities, or analysts must update and revise it to take account of the changing empirical circumstances.

In the remainder of this chapter we explore several families of models useful for understanding social behavior, including Blau space ecological models, social network models, social influence models, cognitive models, game theory, and promulgame models. We begin with Blau space ecological models, which allow analysts to study network processes using demographic and membership data. These data are relatively easily obtained and thus Blau space approaches are useful for producing high-level abstractions. We then consider social network and social influence models, both of which allow for relatively precise estimation of tendencies toward particular relationship structures as well as behavioral and attitudinal predictions. However, both classes of models also require comparatively detailed data about individuals and their relationships and thus demand more data than Blau space models. Next, we address cognitive models and explore

decision-making processes. These models focus on individual, rather than group, behavior and therefore can be relatively data intensive. Using these models with social network and influence models can yield valuable insights, but further increases the data required. Finally, we discuss game theory and promulgame models, which direct attention toward the individuals and groups evaluated in the earlier approaches, the features of the environment, and the interactions between them. Thus, the first main section of the chapter progresses from high-level abstractions through increasingly detailed and data-intensive models before concluding with approaches that deal with situational context.

We then describe the gaps and limitations affecting these models, thereby revealing some of the work that remains to be done. All of these models are subject to ongoing development and none has reached the level of turn-key solutions. Finally, we explore some of the steps that developers must take to transition these models into operational systems.

This chapter is intended to be useful to readers at a wide variety of levels of expertise, ranging from novice researchers to field practitioners. Needless to say, it is impossible to write a chapter that meets the information needs of all potential audiences, so portions of the content may be too technical for some readers and too simple for others. Thus, readers should take this chapter as an introduction that guides them through some of the most promising areas of research and gives a flavor of what these approaches can do. Sources listed in the bibliography provide more technical detail.

2. State of the Art

2.1. Blau Space Models

Blau space, named for Peter M. Blau, is a *k*-dimensional system in which each dimension is a sociodemographic variable and each point is represented by a set of *k* coordinates (McPherson, 1983; McPherson & Ranger-Moore, 1991). Each set of coordinates represents a unique combination of sociodemographic characteristics. Both individuals and organizations can be represented in Blau space at locations that correspond to these combinations. In other words, Blau space represents combinations of variables such as age, education level, and wealth as locations within a multidimensional space.

This multidimensional space conveys information because of homophily (Lazarsfeld & Merton, 1954), or the tendency for individuals to associate with those similar to themselves (e.g., "birds of a feather flock together"). Homophily is one of the most robust of all social science findings (e.g., McPherson, Smith-Lovin, & Cook, 2001) and plays a significant role in determining association in both the United States (Marsden, 1987, 1988) and elsewhere (Brashears, 2008). As a consequence of homophily, nearness in a Blau space model is positively related to the likelihood of association. Blau space therefore allows us to use demographic similarity to yield a probabilistic depiction of interpersonal ties, allowing analysts to produce an overall picture of population-level social networks without the need to collect expensive network data.

In addition to capturing individual networks, Blau space permits the modeling of ecological competition between organizations and cultural products (e.g., musical styles). All organizations require members and individuals are more likely to join an organization, or adopt a cultural product, if their associates have already done so. Even in the labor market network recruitment (e.g., referrals) accounts for approximately half of all hires (Bewley, 1999; Granovetter, 1995; Marsden & Gorman, 2001). Because individuals join groups to which their associates belong, and associates are typically homophilous (i.e., similar in multiple demographic attributes), organizations recruit from a limited and contiguous area of Blau space known as a "niche." Because both individual time and the number of persons in a given segment of a population (e.g., a niche), are limited, organizations whose niches overlap compete for the same finite pool of resources (i.e., member time). The larger the number of organizations that attempt to draw members from the same area in a Blau space model (i.e., the same population segment), the more competition these organizations experience.

The degree of competition in a region of Blau space has predictable effects on organizational memberships.[2] In areas of high competition, current members are more likely to leave the organization (McPherson & Rotolo, 1996; Popielarz & McPherson, 1995) and recruitment efforts will be less successful as rival organizations pursue the same individuals. In contrast, areas of relatively low competition produce more successful recruitment and less attrition. As a result, over time niches tend to move away from areas of high competition and towards areas of low competition.

Competing organizations often differ in their degree of specialization, which has important consequences for the competitive ecology. For example, a chess club may occupy only a small niche, while a church occupies a broad niche. To the extent that their niches overlap, these organizations compete for the time and attention of the same people. Competition is not symmetric, however, and the extent of the church's niche may mean that it only overlaps slightly with that of the chess club, whereas the church entirely encompasses the chess club's niche. Thus, the chess club competes with the church for all of its members while the church only competes with the chess club for a few of its members. A multi-organization system reaches equilibrium when the full carrying capacity (i.e., quantity of potential members) is allocated to the organizations in a manner determined by their degree of mutual competition.

While the organizational ecology can reach equilibrium, periodic changes in the carrying capacity generate shifts in the positions of organization niches and prevent a static equilibrium (McPherson, 2004). However, the direction of niche movement can be predicted, allowing analysts to assess the future composition of a group (Bonikowski, 2010; McPherson & Ranger-Moore, 1991). Thus, Blau space permits us to construct an ecological model of organizational membership and to predict the changing demographics of organizations—at least in part—through a competitive process of recruitment and retention.

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[2] Organizations need not realize that they are competing. As long as two organizations exploit the same finite pool of resources, they are in fact competing.

The affiliational ecology model was originally constructed to explain the membership characteristics of organizations, but has also been applied to cultural products (Mark, 2003) such as musical styles (Mark, 1998), including change over time (Bonikowski, 2010). In other words, cultural products, such as musical styles, can be modeled as competing for supporters in much the same way that organizations compete for members. In theory, a wide variety of phenomena can be modeled in a similar fashion (McPherson, 2004).

McPherson (1983) first proposed Blau space models, and this approach continues to develop. Recent research, funded by the Defense Threat Reduction Agency, has continued to elaborate and refine the basic model. This stream of research has shown that models using Blau space methods can predict both deviant and conventional behaviors at the individual level (Brashears, Genkin, & Suh, 2012; Suh, Brashears, & Genkin, 2012). Importantly, organizational competition also influences the behavior of organization non-members (Brashears, Genkin, & Suh 2012; Suh, Brashears, & Genkin, 2012). In combination with earlier work, this suggests the possibility of predicting individuals' tendencies to engage in various types of behaviors (e.g., suicide bombing) using an inexpensive Blau space approach.

Additional research seeks to generalize the concept of the niche to individuals. In this model, an individual's Blau space neighbors represent a set of others who have regular contact with that person and thus exert consistent influence, regardless of whether they are directly connected to the individual. Such others often share a physical or social context with the individual, or are connected via third parties, and thus serve as both a reference group and a measure of the local informational environment. This method has proven effective in predicting health perceptions and behaviors in a U.S. sample, even when controlling for a wide variety of covariates and direct network effects (Behler, Suh, Brashears, & Shi, 2013). Thus, Blau space models offer a powerful and flexible way to model human behavior using minimal data, but generally produce a high-level abstraction of the modeled social system.

2.2. Models for Social Networks

Human social networks are of increasing interest to scholars and analysts, but drawing valid statistical inferences about these networks poses challenges. Most statistical techniques assume that observations are independent (e.g., the opinion of one respondent to a survey does not determine the opinion of another respondent), but this assumption cannot apply to social networks. Individuals who share a relationship (i.e., are tied) influence one another, and thus standard statistical methods cannot be employed (e.g., Marsden & Friedkin, 1993). Additionally, network data are expensive to collect and few analysts have access to a "sample" of networks. As a result, analysts cannot use standard techniques to compute statistically valid estimates of network-level processes. Both of these difficulties are exacerbated when dealing with data collected over time, which allows more certain identification of causal relationships, but also introduces statistical dependence on a longitudinal as well as a cross-sectional basis. Finally, analysts often wish to explore how network structures (e.g., who is friends with whom) and actor attributes (e.g., characteristics and behaviors) influence each other, thereby creating even more complex dependency structures. For example, are individuals influenced to become suicide bombers by their associates, or do individuals who want to become suicide bombers tend to become

associates? Fitting models to network data calls for specialized techniques, and two types of models have gained considerable traction: Exponential Random Graph Models (ERGMs), which parameterize graph features, and Siena models, which parameterize the tendencies of simulated actors.

ERGMs begin with the observation that any realized network is a specific instance drawn from a population of potential networks. For example, a group of 15 individuals can have a total of $n(n–1) = 15(15–1) = 210$ relationships. If these relationships are binary (i.e., a relationship either exists or does not exist), then the sample space from which the observed network is drawn consists of 2^{210} or 1.64×10^{63} possible networks. The probability of observing any specific network in this space, assuming all are equally likely, is $1/2^{210}$ (Wasserman & Faust, 1997). However, while all networks might be equally likely to occur, certain network characteristics are more likely to occur than others. For example, only one network contains all 210 possible ties and only one network contains 0 ties, but many networks contain 105 ties.[3] Thus, models can generate expectations for how many ties a network drawn at random from this sample space should contain. If the observed network contains many more or many fewer ties than this expected value, we can infer that some mechanism is encouraging, or discouraging, the formation of social ties. The same logic extends to other network processes, including reciprocity (i.e., the tendency for individuals to select each other as associates) and transitivity (i.e., the friend of my friend is my friend), among others. ERGMs estimate parameters describing how much more (or less) often a particular feature is observed than we would expect by chance.

The statements above require two elaborations. First, because many characteristics of a network become more probable when many ties exist (e.g., reciprocity is higher when there are more ties overall), parameter estimation must control for the number of ties in the network. ERGMs impose this control by limiting the sample space to those graphs with the same number of nodes (i.e., vertices) and ties (i.e., edges), as the observed graph. Second, while the ties are binary, the probability that a tie exists does not have to be 0.50. Applying a Bernoulli distribution can model the probability that a tie exists across the potential range, and these probabilities can be conditioned on other factors, including the size and density of the network as well as the attributes of actors and actor pairs, yielding a set of conditional uniform distributions.

The general ERG model (Lusher, Koskinen, & Robins, 2013; Robins, Pattison, Kalish, & Lusher, 2007) parameterizes particular network features. One feature might be a closed triad (i.e., a group of three nodes that all have connections to each other) while another might be an open triad (i.e., a group of three nodes that contains only two ties). The model calculates statistical coefficients representing the tendency for a given graph to contain more, or fewer, of these features than would be expected by chance. It determines parameters using Monte Carlo Markov Chain Maximum Likelihood Estimation techniques, which permit inclusion of a very large variety of

[3] To use a more familiar example, when rolling two (fair) six-sided dice, only one combination sums to 2 (1+1) and one combination sums to 12 (6+6), but six combinations sum to 7 (1+6, 6+1, 2+5, 5+2, 3+4, 4+3). Thus, even though all possible combinations are equally likely, combinations that sum to 7 are much more likely to occur than combinations summing to 2 or 12.

configurations (Snijders, Pattison, Robins, & Handcock, 2006; Wasserman & Robins, 2005), although estimating parameters with larger numbers of nodes and ties can consume considerable time. These techniques generate a set of graphs using randomized starting values for the model parameters and compare them to the observed graph; if the observed graph has a very low likelihood of belonging to this set, the model selects new parameter values and repeats the process. Over many replications, the process homes in on the parameter values most likely to have produced the observed graph. Modelers must exercise care, however, to ensure that parameter estimates remain stable against local maxima (i.e., models should be estimated several times with different initial seeds). They may also have to include some configurations in the model regardless of theory in order to avoid near degeneracy, or a situation in which only a small subset of all possible graphs has other than a very low probability (Handcock, 2003). A good fitting model can be defined as one that yields a very high likelihood of obtaining the observed graph relative to the alternatives.

Scholars continue to develop the ERGM framework. Wang, Robins, Pattison, and Lazega (2013) have generalized ERGMs to accommodate two-level scenarios (e.g., individuals nested within groups). This approach resembles hierarchical linear modeling and allows analysts to examine interactions between individual relations and higher level structures (e.g., organizations). However, the software implementation of this model is currently somewhat unreliable. Other work (Caimo & Friel, 2012) has wedded ERGMs to a Bayesian framework to assess the quality of model fit. This helps to avoid reliance on frequentist model fit measures, which depend upon as yet poorly understood comparison distributions. Thus, in addition to considerable empirical work using ERGMs, the method continues to acquire methodological sophistication.

ERGMs capture social processes by parameterizing features of the network, but impose no assumptions about the mechanisms that generate these features. This adds to the model's flexibility, but can leave the analyst in the position of trying to justify configurations that lack a clear theoretical meaning. Stochastic actor-based models for network dynamics (i.e., Siena models) avoid this problem by building stronger assumptions into the model. Additionally, Siena models are ideal for longitudinal data.

A Siena model represents interpersonal ties as states rather than events, meaning that it shows any particular communication event (e.g., an email exchange) simply as an expression of an underlying, ongoing relationship. States can change (i.e., ties form and are dissolved) but in general existing ties tend to continue existing and nonexistent ties tend to continue not existing. Time varies continuously in arbitrarily defined segments and actors control their outgoing ties (i.e., individuals choose whom they prefer) but not their incoming ties (i.e., individuals cannot choose who prefers them). Finally, Siena models employ simulated actors, or simplified mathematical representations of the entities (e.g., individuals) that make up the nodes of the network.

A Siena model proceeds via two mechanisms: the change opportunity process and the change determination process. The change opportunity process determines the rate at which actors in the model have the opportunity to alter their network ties or behaviors. In its simplest form, this rate is uniform across all actors, meaning that at any given time all actors are equally likely to make a

discrete change (i.e., all individuals change at the same rate). Alternatively, the rate can be conditional, meaning that some actors (e.g., more popular individuals) are more likely to make discrete changes than others (i.e., exhibit a higher rate of change). The rate of change can also vary over time (e.g., change occurs at an increasing rate). The model determines stochastically which actor will make a change, with the rate controlling the probability that any given actor will be chosen.

The change determination process models the changes that the actors make when given the chance. Actors may make a single change per opportunity: add a single tie, eliminate a single tie, change one attribute, or do nothing. This one-change rule defines a finite set of alternative networks that actors can reach at the present time. The actor's *objective function*, which defines how rewarding particular network structures are for the individual actor, determines which change is made (i.e., which alternative network is selected). Put simply, the actor will tend to select the alternative that produces the most positive objective function. However, because the model is stochastic, actors do not always select the change that yields the greatest improvement in the objective function. Thus, while the objective function can be thought of in terms of "preferences," it is more accurate to view it as capturing tendencies stemming from preferences as well as circumstances beyond individual control (e.g., the availability of certain types of others in the population).

The effects in a Siena model refer to the tendencies of simulated actors to make specific types of changes (Snijders, Van de Bunt, & Steglich, 2010). The effects can be defined by structure (e.g., reciprocity, transitivity), by attributes (e.g., level of behavior adoption), as well as interactions between the two (e.g., homophily).

The Siena approach uses a method-of-moments procedure to generate parameter estimates and therefore models the process of change between time points rather than tendencies at any one time. The first time point is not modeled, serving instead as a start for the estimation process. As a result, a Siena model cannot be estimated without data from at least two points in time.

In outline, the Siena model proceeds by taking the first wave of data (t) as the starting point for the simulation model. An actor is chosen at random, with the probability determined by the parameters of the change opportunity rate (uniform or conditional). The model computes the objective function for both their current network structure as well as all network structures reachable via only a single change, with the probability of a given change determined by the size of each objective function, including the function for the existing network structure. Once the model has selected a given network using this procedure, the change (if any) is made and a new actor is chosen via the change opportunity process. Change in the network is modeled as a Markov process: the state of the network at the current time (t) probabilistically determines the future (t+1) state of the network, with no additional effects felt from prior (t–k) states. This process repeats many times, in theory yielding outcome networks comparable to the observed networks at later time points (i.e., t+1, t+2, etc.).

Initially the analyst sets the parameters in the objective function randomly and the software compares the performance of the simulation to the observed data. If the simulation fares poorly

the values are adjusted and the simulation process is repeated. Eventually, the model homes in on the best set of parameter values (including those for the rate of change parameters) for reproducing the observed networks. As with ERGMs, however, modelers must take care to ensure that parameters have not been trapped in local maxima; re-estimating with new seed values is advised.

Recent elaborations of the Siena model have explored its applicability to two-mode data (Snijders et al., 2012), allowing researchers to connect individual and organizational processes in a single longitudinal model. Brandes, Indlekofer, and Mader (2012) have also developed diagnostic visualization tools that assist researchers in determining the quality of model fit. Thus, the Siena approach is still undergoing considerable development.

Siena models and ERGMs differ in their overall perspective on social networks. Siena models view the actors as making changes to their networks in pursuit of particular structures. This has the advantage of producing parameters that allow many small changes to a network to accumulate into overall network configurations, but runs the risk of treating actors as having more control over the social system than they really do. ERGMs, in contrast, focus on tendencies for particular features to appear more often than expected by chance, but make no effort to model the processes that give rise to these features. Therefore, analysts can identify features that are preferred more often than others, but that cannot be realized through any straightforward process. The model preferred for a given application should depend on data availability, on whether the data are longitudinal or cross-sectional, and on whether the nodes in the network can reasonably be thought of as “agents” (e.g., transformers in a power grid are not “agents” in the same sense as human individuals in a social network).

2.3. Social Influence Network Theory

To understand the hearts and minds of a population we must study attitudes. Social Influence Network Theory (SINT) fills this gap by modeling valued attitudes, meaning affective (i.e., emotional) views of some issue that can range from very positive to very negative. The theory assumes that individuals enter an interaction with some initial attitude and are susceptible to influence from others. The degree of influence is determined by three characteristics: the network of relations among individuals, the weights placed on these relations, and the attitude of each relationship partner.

First, individuals are tied to others in a social network. We exchange information, views, and camaraderie with our associates, and their attitudes can influence our own views. Additionally, however, our associates have relationships to others to whom we are not connected (i.e., our second-order network). As those others influence the attitudes of our associates they will, indirectly, influence our own attitudes. To understand the process of attitude change and consensus, we must model the entire network.

Second, we do not necessarily listen to each of our associates equally carefully. Some of them have a strong influence on our own views, while we may tend to ignore others. As a result, the model

must take account of the unequal influence of various associates, and must factor in our relative level of self-confidence.

Finally, the extent to which initial attitudes must change in order to reach consensus is at least somewhat a function of starting positions. Individuals who begin relatively further apart on an issue must change more in order to reach consensus than those who begin near each other.

The combination of these straightforward elements yields complex and interesting behavior, as each can moderate or enhance the impact of the others. For example, very different initial positions may result in relatively little attitude change if few direct network connections exist between opposite extremes and if the self-weights are very high. Alternatively, when others are very influential, attitudes may change so rapidly that the system will repeatedly overshoot consensus, ultimately requiring longer to reach equilibrium. Therefore, while the model is conceptually simple, it has rich implications.

The SINT model (Friedkin & Johnsen, 2011) includes several important elements. First, an actor's self-confidence is locked in a zero-sum game with the influence of others; actors less certain of their own views are more susceptible to the attitudes of others. Second, all persons to whom an actor is tied have an influence on the actor's future views, with the degree of influence determined by the product of their level of influence and their current attitude. Third, the views of the actor at the first time point (t=1) exert a continuing influence in the model at all points in time. This last element is extremely useful in preventing the model from predicting an unrealistic degree of consensus, but also treats the first time point as special relative to the remaining points. In fact, because the analyst chooses the first time point based on convenience or data availability, its theoretical value is dubious. Finally, the model is computed iteratively; each computed set of attitudes is reentered to predict the attitudes at the next time step until the system reaches equilibrium.

SINT allows an analyst to predict the equilibrium states of members, but two or more consensus positions are possible at equilibrium, implying some ongoing disagreement. In all but a very few boundary cases the equilibrium consensus positions lie on the convex hull of the initial positions.[4] Put differently, the equilibrium consensus will not be more extreme along any attitude dimension than the most extreme initial positions in those dimensions. The model has an additional advantage in that it can derive many of the quantities needed from partial information. For example, if data on initial and ending attitudes are available, as well as network data on the actors,

[4] In dyads where both partners heavily influence the other, consensus positions sometimes, though rarely, appear outside the convex hull. This appears to result from an attempt to escape from a coordination problem. In these systems interaction partners repeatedly overshoot each other in an attempt to reach agreement, and so one partner adopts a more extreme position in order to provide a conspicuous target for the other. For example, a married couple might try to choose a restaurant for dinner. Each suggests a restaurant and each attempts to defer to the other's preference, thus preventing consensus and delaying the meal. One partner might attempt to break the cycle by suggesting a third option that usually neither prefers. While this example is only loosely accurate (i.e., the example deals with a decision rather than an attitude), it does help illustrate the general process.

the model can derive the weights on those relationships. Thus SINT provides a flexible and effective way to model attitude change and stability in groups.

2.4. Cognitive Models

Researchers have used a variety of mathematical and computational models to emulate the cognitive process. The examples summarized below highlight some of the most influential.

An early example focused on Belief, Desire, and Intention (BDI). Emerging from artificial intelligence, the BDI model treats the three constitutive concepts as key pragmatic dimensions of cognition (Bratman, 1987). Belief encompasses those assertions that the actor considers true and that, in some cases, act as a placeholder for the actor ontology (although the actor may not be consciously aware of them). Desire conveys focus and is sometimes used interchangeably with goals. Intention describes the phase in which belief and desire have congealed into a settled plan, or course of action.

BDI models haves been criticized for doing both too much and too little. For example, some critics say that having incorporating only three steps makes the mechanism underlying BDI models too simple, while others view three interacting dimensions as overkill (Rao & Georgeff, 1995). However, BDI models suffer from their ultimate limitation in that, while seemingly intuitive, they have no obvious foundation in either decision theory or substantive social action that would shape and drive their computational implementation and/or the resulting dynamics. Such criticism suggests that BDI is constructed on the basis of folk psychology and, thus, cannot provide models with more than a pseudo-cognitive placeholder.

The rational choice model of cognition, as developed by Becker (1976), Coleman (1990), and numerous others (cf., Elster 1986), has played an influential role in the social sciences, albeit arousing controversies along the way (Coleman & Fararo, 1992; Green & Shapiro, 1994). The formulation of individual models depends on the domain and the research strategy, but all rational choice models provide a mechanism for assessing the costs, benefits, and tradeoffs of different courses of action, and the responses that result from such assessments.

One strength of rational choice lies in its high level of generalizability. Researchers have used the paradigm in a wide range of social domains, from microeconomics (Field, 1984) to international relations (Levy, 1997). Often researchers have been able to identify rationalities underlying strategies that, on the surface, appeared to be irrational or self-defeating (Pape, 2005).

However, a primary weakness of rational choice is that it typically involves closed concepts of gain and loss. Modelers often act as if these concepts are self-evident and, as a result, many models weakly represent the dynamic spectrum of priorities that social actors embrace, including their evolution over time. Another problematic characteristic concerns how the models represent emotion as a factor in decision processes. Often they simply ignore affect and, when they do address emotions, frequently view them primarily as a source of irrationality (Doran, 2000). This undermines possible analysis of strongly committed action and/or the complementary ways in which emotion and cognition work to achieve insights and effective action.

Randall Collins has been a major contributor to cognitive models in the social sciences that integrate both emotion and ritual, creating a more extended concept of cognition. He developed his theory of emotion in social life over a period of time (Collins, 1981a, 1981b, 1990; Kemper & Collins, 1990), ultimately proposing a mechanism designed to subsume rational choice models (1993).

Collins' incorporation of emotion into sociological theory is based upon Durkheim's discussion of religious ritual (1995) and Goffman's subsequent analysis of interaction rituals (1967), as unified in his own theory of interaction ritual chains (IRCs) (Collins, 1981a, 1981b, 1990, 2005). In brief, Collins argues that group solidarity at all levels is grounded in emotion, that emotional bonds precede and make possible coercive and contractual relations, and that IRCs of widely varying types generate group solidarity as well as emotional energy (EE) among the participants. The efficacy of specific IRCs varies depending on the attributes of group interaction: physical assembly, boundedness, focus of attention and awareness, commonality of emotional mood, and symbols that represent group membership (Collins, 1988; Collins, 1993).

Collins (1993) presented IRC/EE as a common metric and motivation underlying all social exchanges. His model recognizes "emotional solidarity with a group as the primary good in social interaction" (1993, p. 205). He notes that individuals "are motivated to maximize the amount of solidarity they can receive, relative to the costs of producing it" (1993, p. 209).

Nonetheless, Collins's IRC/EE model has weaknesses that prevent realization of its putative advantages. First, contrary to Collins's assertions, there is little reason to believe that the interchange of interaction rituals fully determines economic markets. Second, serious questions arise as to whether IRC markets operate in the narrow way that the model suggests. However, Collins's model has served as a springboard to a more general affect-based field theory (Sallach, 2008) that avoids the limitations of the IRC/EE model in its speculative 1993 formulation while, at the same time, integrating emotional and cognitive processes for social actors at multiple scales. This integration allows behavior previously regarded as generically "irrational" to more specifically recognize the underlying emotional commitments that override utilitarian considerations, sometimes in a strongly persistent manner (cf., Benmelech & Berrebi, 2007).

2.5. Game Theoretic Models

The formalisms most frequently associated with adversarial interaction derive from game theory. They have been applied widely, and are one of the rare forms of social analysis that can explore decision processes and outcomes using deductive analysis, while increasingly supporting advanced simulation environments as well (cf., Parsons, Gmytrasiewicz, & Wooldridge, 2002). Fudenberg and Tirole (1987) summarize the several sources of game-theoretical strength:

> [Game theory] imposes some discipline on theoretical thinking. It forces economists to clearly specify the strategic variables, their timing and the information structure faced by firms . . . [T]he researcher learns as much from constructing the model (the "extensive form") as from solving it because in constructing the model one is lead to examine its realism. (p. 176)

However, it also appears that the more complex and dynamic the social phenomena under study, the more difficult it is to achieve effective game-theoretic representation. Peltzman (1991), for example, bemoans the seeming inability of theory, especially game theory, to lead to powerful generalizations. He finds, rather, " . . . an almost interminable series of special cases. The conclusions drawn from these cases tend to be very sensitive to the way problems are defined and to the assumptions that follow" (p. 206). Peltzman continues: "By suitably permuting and combining the problems and assumptions, new models can be produced almost *ad libitum.* Indeed, the production of new models and the tidying up of old ones seem to be major goals of this research enterprise" (p. 207). Similarly, Fisher (1989) writes: "There is a strong tendency for even the best practitioners to concentrate on analytically interesting questions rather than on ones that really matter for the study of real-life industries" (p. 123).

Game theory has provided a mathematical way of exploring interactive social outcomes under varying assumptions. However, its very formalism has led to concerns about unrealistic assumptions (e.g., perfect foresight, stylized outcomes) and a failure to incorporate the situated contexts that inform strategic decisions. To maximize its theoretical and practical contributions to social modeling, game-theoretic models need to become more dynamic. The resulting models should be elegant, and guided by social theory and, as a result, they will also be considerably more expressive.

Human actors play multiple games, select among available games, shift from one to another, sometimes mistake what the game their counterpart is playing, act in ways that are (more or less) effective within multiple games simultaneously, etc. Luttwak (1987) points out that strategic choices are inherently paradoxical: because the strongest, most effective options are also the most obvious and, thus, are likely to be the best defended. Options that are suboptimal, and thus unexpected, are sometimes the most effective. This emphasis upon surprise is not just a product of strategic planning. As Miller (1997) has documented, unpredictability has been essential to species survival and adaptive dominance. Accordingly, interpretive dynamics that produce unexpected results can be seen to be essential to the accomplishment of participatory and analytical understandings of strategies and courses of action.

2.6. Promulgames

Promulgame theory represents a cluster of innovations within game theory designed to reduce the brittleness sometimes found in formal games and to recognize the recurrence and interaction of broad game types (Sallach, 2006). The two aspects of interest are *pro*totypical games and *mul*tigames. Combining the two types of games results in a *promulgame*,[5] which in turn serves as an interactive building block of broader sociocultural structures and processes.

[5] Please pardon the compound neologism.

Prototype theory defines the nature of games that actors play, potentially at diverse levels. There are three prototypical games: beneficent, instrumental,[6] and coercive, with gradations of each type. Together, they define a broad range of social game types and allow exploration of the interactions among them. These games can be easily represented by a unit interval of [1, –1] divided into three ranges of, for example, [0.95 to 0.35, 0.3 to –0.3, and –0.35 to –0.95]. In this example, the games range from the most beneficent to the most coercive, with each game having an internal range of 0.6.

Promulgames are prototypical in the sense that a conceptual core defines the game type, while empirical games vary in their proximity to that core (Rosch, 1978; 1983). Researchers can identify and dimensionalize these differences for modeling purposes. This form accommodates itself to the representation of an extensive variety of empirical games, including the emergence of calibrated strategies.

Beneficent games involve a kind of mutual support seen in families and tribes, among neighbors, and within communities. Types of support in beneficent games may vary, but accounting is not strict and the game tends to be mutually reinforcing over time, commonly resulting in virtuous spirals (Carse, 1986). Instrumental games are familiar, involving complementary benefit and, relative advantage, arm’s-length accounting, and are often self-reinforcing (Osborne & Rubinstein, 1990). Coercive games involve the exchange (or threat) of force or violence. Reciprocity is frequently anticipatory, and comparative accounting tends to be exaggerated, resulting in a vicious spiral. Complementarity usually takes the form of innovative tactics or novel defenses. Any of the three types of games can stabilize over time to a recurrent balance.

In addition to reciprocal interchanges, where the details primarily concern frequency, quantity, and/or quantitative conversion, off-diagonal interchanges occur in which an actor uses one resource to acquire or respond to a different one. For example, actors use force to gain material benefits, or money to gain altruistic benefits. Therefore, each game resource requires two (directional) dimensions. Such games are apparently less likely to stabilize than are reciprocal games, but are nonetheless interesting by virtue of their empirical familiarity. For example, armed robbery uses coercive means to acquire instrumental resources. Mercenary armies and/or hit men use instrumental means to acquire coercive resources. Revolutionaries and terrorists use instrumental and/or support services—providing food, welfare, and health services—in return for assistance in conducting coercive acts or hiding the perpetrators. Finally, abducting children to raise them (as opposed to demanding ransom) can be viewed as a use of coercive means of acquiring human resources.

Off-diagonal games also figure in situations characterized by ambiguity or deception as to which games are being played. Examples abound. Contributions to charities (support) may be deceptively converted to terrorist use (coercion). The sale of contraband can be an economic means of achieving the same result. Therefore, human actors (and, thus, computational models), need the

[6] This game type is often called ‘economic,’ but this characterization is too narrow. Other forms of instrumental and/or pragmatic trade-offs and negotiations, particularly in political and military domains, provide additional examples of instrumental games.

capability to determine the game they are being invited (enticed) to play. Computational models must assemble and parameterize instantiated games endogenously from their components (Sallach, 2000).

Social actors engage in games as a means of eliciting coordination from other actors (cf. Taylor, 2005). They initiate (or respond with) games of different types based on various situated factors. Table 1 illustrates two such factors: a) the strategy employed by the actor (top row), and b) the relationship between the actor and relevant other actors (bottom row).

Table 1. *Promulgames by Strategy (Top) and Relationship (Bottom)*

STRATEGY:	**Compliant (Soft)**	**Defensive (Firm)**	**Aggressive (Hard)**
Beneficent	Unrestrained support; give freely without expectation of return	Attend to timing and adequacy of response; be prepared to diminish reciprocity	Withdraw cooperation; shun
Instrumental	Relax competition; share opportunities; tolerate slow or incomplete responses	Compete; expect value-for-value; negotiate binding contracts	Demand hard bargains; seek to drive competitor out of region or specialty
Coercive	Show respect for adversary; accept truces; allow conflict to subside	Return blow-for-blow; assess threats; prepare for possible attacks	Attack without provocation; amplify threats; invent reasons to confront or destroy enemy
ROLE:	**Affiliate**	**Rival**	**Adversary**

The relationships among actors described in Table 1 overlap with a number of social theories and models. Recognition theory provides an important example. Honneth (1996) distinguishes among three patterns of recognition: love, rights, and solidarity. The affinity relation that Honneth calls ‘love’ gives rise to the strategies summarized in the top row, calibrated by a selected response to the particular situation. The legal recognition relationship (‘rights’) is primarily instrumental in nature (summarized in the middle row), where various actors agree to support legal rights for all as a means of securing their own (1996).

Groups based on solidarity (and its diverse bases) may draw upon any of the protogame strategies, depending on their historic and current relationships. Groups can view each other as allies (with whom they have an affinity), competitors and/or actors with asynchronous dependencies (cf.

Emerson, 1962) (with whom they engage in a pragmatic or instrumental way), or enemies (whom they view as having to be coerced, or be threatened with coercion). In each case, the calibration of particular moves depends upon the specific situation, and on the actors' understanding of it.

3. Modeling Gaps

Research has made considerable progress in modeling a wide variety of social systems, ranging from individual cognition to organizational competition. Nevertheless, these models are not perfect. Below we note several gaps for each of the models introduced in this chapter.

Blau space models offer data-efficient approaches to modeling abstract dynamics at a high level, but applying them involves more art than science. No rigorous method exists for determining which variables to select as Blau dimensions. The only theoretical guideline is that the dimensions be "salient" to the population under study, meaning that the variables must have an impact on association (Blau, 1977). In general, any variable on which association is homophilous is a salient dimension, but this is a weak criterion. Further, the modeling approach has no guidelines for the number of dimensions to include. Larger numbers of dimensions tend to reduce the overlap between niches while smaller numbers increase it, but no method exists for determining an appropriate number. This approach would therefore benefit from methods to rapidly and reliably assess whether a given Blau space model has the correct dimensions.

The types of variables that can be used as dimensions also depend on whether the analysis focuses on individuals or organizations. When depicting organizations, the models can include categorical variables (e.g., race, sex) by rendering a dimension as the percentage of a group that falls into a particular category (e.g., percentage of the organization that is female). However, this approach does not work when modeling individuals because they have discrete values (e.g., male *or* female); as a result, a Blau space model of individuals can use only continuous variables (e.g., income, age) as dimensions. New methods of scaling Blau space dimensions are needed to eliminate this restriction.

Social network models have made tremendous strides in recent decades, but require substantial improvement. First, ERGMs parameterize specific network configurations, but highly preferred configurations sometimes lack a clear meaning. In other words, a particular configuration may be necessary to achieve acceptable model fit, but there may be no clear process through which this configuration could emerge. Research should determine whether these odd configurations signal a deep insight about social behavior that remains to be achieved or simply indicate that the model is degenerate.

Additionally, while ERGMs and Siena models are powerful techniques, they both rely on simulation. This requires a considerable amount of computation time, which can be prohibitive in large and complex networks. Developers should devote additional work to optimizing these techniques for rapid computation, preferably by exploiting multi-core and parallel computing architectures whenever possible.

SINT delivers a powerful and flexible model of attitude change and stability, but several hurdles remain. First, can SINT be adapted also to model behaviors? Individuals may be more likely to adopt a particular behavior or practice as their attitude toward it improves, but no link function that relates attitudes to behaviors currently exists. It should be possible to specify such a link, but doing so would impose assumptions about the causal linkage between attitudes and behaviors. Given the pronounced issues of reverse causation in this area (i.e., attitudes may follow from behaviors), developing such a link function is a theoretical and empirical task as much as a mathematical one. Second, including an actor's attitude at the first time point in every iteration prevents perfect consensus from emerging in all cases, but also gives one arbitrary moment a disproportionate influence over the model. SINT would benefit from development of an alternative approach to preventing perfect consensus from emerging in all cases.

The majority of the models reviewed in this chapter were originally developed with face-to-face interactions in mind, but interactions increasingly occur in electronically mediated forms. It would be useful to take advantage of the wealth of online data on social behavior, but models developed around offline interactions may not translate to online contexts. Some models (e.g., SINT) have enough flexibility to handle the transition with minimal modification, but other models are likely to be context dependent. This necessarily means that we must exercise restraint in using online data until our understanding has improved, but completing this basic research will produce substantial long-term advantages, as electronically mediated communication can only continue to grow in importance.

The integration of cognitive and game-theoretic models raises four essential issues: 1) How can a broad range of social theories be integrated with each other and incorporated into computational models of social dynamics? 2) How can social models best handle cross-scale interaction? 3) How can endogenous models of situated understanding best capture the rich interactions among social actors and still remain computationally tractable? 4) What are the mathematical foundations for effective models of social dynamics? These questions define further gaps for research to address.

The first and last questions are fundamental. Answering them will provide the ultimate basis for the advancement of computational models. The second and third questions are more application oriented. They provide a focus to the more abstract questions, as well as the criteria for prospective answers. Research addressing all of these questions will result in a new generation of computational architecture, and a new foundation for computational social science.

3.1. The Road to Transition

What steps must developers take to convert the models discussed here into operational systems ready for use by practitioners? One of the most extensive, and necessary, improvements involves creating robust systems for converting between data formats. The models described above are implemented in a number of different programming languages, and one of the greatest routine difficulties in using them stems from the need to transform data to be compatible with each. If and when translation protocols emerge, developers must exercise care in minimizing the computational time required to store and transform the data.

Each of the described models has achieved significant empirical success, but, at present, guidelines for identifying degenerate or poorly fitting models remain loose. For practitioners to apply these models effectively, they must be able to determine clearly whether the models are fitting adequately and to diagnose the inevitable problems that arise in any analytic task. Therefore, developers must also create and automate diagnostics for the models described in this chapter.

Despite their separate developmental histories, many of the models presented in this chapter have deep similarities. For example, ERGMs work on networks assumed to be in equilibrium, whereas Siena models focus on disequilibrium. Similarly, both SINT and Siena focus primarily on the transition to stability, although SINT includes explicit equations for equilibrium cases. These connections suggest the possibility of integrating these models into a general framework useful in a variety of contexts. Successful integration would reduce the training time necessary for practitioners to perform many of these types of analyses competently.

This discussion of gaps defines a framework for progress in cognitive modeling and game theory. Beyond that framework, the transitional path concerns the type of computational architecture in which these questions cannot only be addressed, but can also evolve as innovations give rise to new issues. The broad computational form will probably be based on agent-based modeling and simulation, a topic deemed beyond the scope of the present chapter. However, developers should view the present forms of agent simulation as bare bones relative to the capabilities ultimately required. The framework defining the gaps also identifies the transitional path. We can expect that agent simulation in the future will be far more theoretical and extensively grounded in mathematical relations and transformations (cf. Sallach, 2012). As game formality increases, it will not only specify simulations, but also form a basis for deductive analysis. Each of these advances will transform and extend computational social science, allowing it to realize its full potential.

4. Conclusions

Research has made substantial progress in developing and refining computational models of human behavior, and has produced a palette of models useful for a broad range of specific contexts and data limitations. Additional work is needed—both basic research to improve our understanding of the workings and implications of the models and applied research to make them easier for practitioners to use—but the basic groundwork has been completed.

The models discussed in this chapter aid in understanding the operation of social groups in a variety or respects. They can provide clues as to the processes that yield specific network configurations and the likelihood of different configurations, can describe the degree of competition between organizations and other abstract entities, and can explain the inner workings of attitude change. We must reemphasize that each model described here is useful in particular circumstances and depends on specific assumptions. Practitioners should therefore assess the usefulness of a model on the basis of these assumptions and of their validity in a particular modeling context. Assumptions will often be strained, if not actually violated, but practitioners should take care to ensure that these violations remain within acceptable bounds. This chapter has surveyed many models, and made no attempt to describe the various assumptions made

exhaustively, but interested readers can consult the literature cited to learn more about these specific techniques and their advantages and disadvantages.

Computational models lend themselves to diverse theories and their integration. Even as researchers assess the theories that animate them more broadly and theoretically, the models must retain their expressiveness. Drawing on the insights attained, their formulation as mathematical models, more elegant and more compelling, will contribute greatly to the advance of mathematical sociology. In 20 years, we can expect that social models will have become considerably more effective because of the mutual strengthening of theoretical sociology and the mathematical formulations of these theories.

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3 Visualization for sociocultural understanding[1]

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1. Introduction

Visualization for sociocultural understanding involves the data, tools, and techniques necessary to convey the behavioral relationships underlying daily life, relationships expressing the evolution of a culture, and the social structures in which these relationships occur. Creating visualizations to better understand sociocultural behavior helps decision makers and end-users build situational awareness and effective operational engagement.

Because sociocultural behaviors are multidimensional, historically contextualized, and emblematic of the ontological structure of the society, visualizing the understanding of that sociocultural context indeed presents a daunting task. While no accepted set of protocols exists to measure success in such an undertaking, specific aspects of individual and collective engagement can be deemed successful if those engagements lead to an appreciation of the other's perspective.

This chapter highlights some of the advances in virtualization technology, social interactive modeling, and perceptual science that have opened vast frontiers in visualization, especially in multidimensional space. Visualization as a theoretical construct has precedence in Card, Mackinley, and Shneiderman (1999), which provides an exhaustive study of research on multidimensional visualization, while Tufte (1997, 2001) has written extensively on graphical representation of quantitative and qualitative data as part of information design. In this chapter, we build upon these earlier works to explore approaches to visualizing data useful in furthering understanding of the sociocultural environment.

Visualizing a society's sociocultural structure has two primary benefits. Human interactions and relationships provide the context for social inquiry. By visualizing these interactions and relationships, the researcher can better identify the most effective means for establishing a presence, assembling and tailoring the necessary tools for engagement, and determining desired outcomes and measures of success. Secondly, constraining the complexity of social engagement through visualization brings the key elements of the potential engagement into focus and provides the roadmap by which intervention can occur.

Visual representation of complex human interactions leads to a more informed understanding of the defining characteristics of the society and the nuances of its cultural practices. The diversity of

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social interactions, however—whether traditional dances celebrating the harvest, the prolific use of hand gestures in public conversations, or the ever-increasing acceptance of social media as a proxy for presence—makes isolating attributes that uniquely characterize a given society an unrealistic goal. Sociocultural practices are fluid and malleable by the external influences that sway practices and behaviors. Practices, attitudes, and behaviors once considered acceptable, whether denying human rights to select groups or according divine attributes to others, have undergone alterations, adaptations, or outright rejection as societies evolve (or devolve).

Capturing what makes a society unique is further complicated by the many different theoretical frameworks in which visualization of such understanding occurs. Purchase, Andrienko, Jankun-Kelly, & Ward (2008) posit three distinct conceptual mechanisms in visualizing understanding:

1. Visualization as an interpreted activity representing the physical form;
2. Exploration and manipulation of the external representation to understand an underlying model of the external form; and
3. Investigation of the posited model to discover interrelationships, trends, and patterns.

These three frameworks are not categorically distinct. Visualizing understanding is a dynamic process, and fully exploring the social interactions in a culture requires elements of all three frameworks. From a sociological perspective, visualization draws upon data-centric interactions between an observer and her participant, which can be organized into a predictive capability by coupling data analysis with a modeling approach that is transferrable across cultural systems and identifies underlying dynamics of symbolic and economic exchange.

Many different types of data are available to provide a relative snapshot of a society's organizational structure. These data are ubiquitous resources in traditional sociological investigative methods and often provide historical context to facilitate the identification of trends within the society as its institutions mature. Examples of these data include demographic data, economic data characterizing household compositions and major industrial drivers of a society, environmental data encompassing quality-of-life factors, and sociological surveys that give insight into the population's overall assessment of their society and the individual's place within that society. In addition to these traditional methods of understanding the sociocultural variability of a people are the relatively new tools offered by social media networks and the vast potential of visualizations afforded by virtual interactions.

For many marginalized populations, traditional datasets are at best sparse and of poor quality, and more often nonexistent. The kinds of data and data collection methods made available by social media supplement or even bypass traditional data collection methodologies, generating an array of new datasets that, when visualized, provide fresh sociocultural insights. Social media formats such as Facebook, Twitter, and Flickr as examples, offer researchers new tools to connect with, engage in, and understand an array of interests and current events in near-real time. These new media also create new challenges, as the ever-expanding stream of data magnifies the traditional difficulties of understanding the cultural and linguistic signatures of a society embedded in those data. To reap the advantages of the new data streams, researchers must now develop tools for efficient ingest of large amounts of social media data, tools and theory-based methods for interpreting the data, and

tools for effective visualization of vast datasets, while simultaneously protecting the privacy of individual subjects.

The chapter begins with a discussion of the various data types available for sociocultural visualization of understanding. Section 2 elaborates upon the different data types used to encapsulate our contextual understanding of social actors. Section 3 presents an example analysis of a linguistic network in which group identification is transformed into recognizable patterns yielding actionable intelligence to guide subsequent engagements. Section 4 introduces traditional data representation methods geared to quantifying the social environment, whether demographic analysis or economic snapshots of individuals, groups, or countries. Section 5 explores data visualization in a multi-dimensional space and the tools necessary to represent that space. Section 6 provides an overview of the new streaming methods of data amalgamation and visualization, while section 7 completes our discussion of the challenges created by this streaming data: unconstrained visualization without a priori hypothetical structure.

2. Data Collection Methods

Understanding a particular sociocultural environment requires data. Regardless of the method employed, data collection defines the key elements of concern for researchers who hope to garner insights about a given social system. It also parameterizes how the researcher can visualize the extracted data to test various hypotheses about the social organization under examination. As with any scientific investigation, researchers should understand the visualization requirements in order to specify the data to collect, the duration of the data collection, and the means for visualizing the data amassed.

Given the amount of data accessible for visualization we must first define the various data elements of interest. Data collection methodologies organize data into the formats in which they will be stored, processed, and ultimately visualized. These formats fall into three categories: structured data, semi-structured data, and unstructured data.

2.1 Structured Data

Structured data formats store data elements in a systematic organization; for example, within a database management system. These data are often gleaned from and stored in data tables with constraints placed upon the storage requirements, whether in terms of specific data types (date, number, character, blob) or of specific data categorization (nominal, ordinal, integer, ratio). Structured data are easy to manipulate using a structured query language and are amenable to a multiplicity of data visualizations (e.g., charts, graphs, maps, tables).

Table 1 shows an example of a data collection from the Tropical Atmosphere and Ocean (TAO) buoy array (McPhaden et al., 1998). Seventy moored buoys are strategically deployed in the equatorial Pacific Ocean to capture a multiplicity of climatic data that parameterize the atmosphere – ocean interface. Sensors on each buoy collect data at defined intervals and transmit those measurements to the ARGOS satellite relay system. The data are then processed and

assimilated into climate models to better visualize the dynamics of the Southern Oscillation and its perturbations, El Niño and La Niña.

Table 1. *Data collection metrics for structured data elements*

<table>
<tr><td colspan="10">Location: 0N 156E 9 Feb 1993 to 20 Mar 2004 (4058 times, 7 blocks) Gen. Date Mar 21 2004 Units: Winds (m/s), W. Dir (deg), AirT (C), SST (C), Rel. Humidity (%), -99.9 = missing. Winds Use Oceanographic Convention:(1,1) is NE at sqrt(2) m/s. Time: 1200 9 Feb 1993 to 1200 12 Dec 1994 (index 1 to 672, 672 times)</td></tr>
<tr><td colspan="2">Depth (M):</td><td>-4</td><td>-4</td><td>-4</td><td>-4</td><td>-3</td><td>1</td><td>-3</td><td>QUALITY</td></tr>
<tr><td>YYYYMMDD</td><td>HHMM</td><td>UWND</td><td>VWND</td><td>WSPD</td><td>WDIR</td><td>AIRT</td><td>SST</td><td>RH</td><td>SDATH</td></tr>
<tr><td>19930209</td><td>1200</td><td>2.5</td><td>-1.0</td><td>2.7</td><td>112.3</td><td>27.70</td><td>29.25</td><td>81.7</td><td>22222</td></tr>
<tr><td>19930210</td><td>1200</td><td>4.2</td><td>-0.5</td><td>4.2</td><td>9.2</td><td>26.98</td><td>29.17</td><td>86.1</td><td>22222</td></tr>
<tr><td>19930211</td><td>1200</td><td>0.4</td><td>-3.0</td><td>3.0</td><td>171.8</td><td>27.21</td><td>29.07</td><td>87.1</td><td>22222</td></tr>
<tr><td>19930212</td><td>1200</td><td>-1.1</td><td>-3.0</td><td>3.2</td><td>199.6</td><td>28.11</td><td>29.15</td><td>82.2</td><td>22222</td></tr>
</table>

Note: Data from McPhaden et al. (1998)

The key to understanding a structured data collection plan lies in the measurability of each element collected. Measurable attributes of the data collection process include the duration of data collection, the sample's spatial domain (if applicable), and the start and end dates for data collection. Additional data may be presented on data quality as a means to guide the usability of the selected dataset. Data quality attribution enables researchers to assess the overall value of the data collection process.

2.2 Semi-Structured Data

Semi-structured formats do not normalize the data into clearly defined tables, but rather group them by semantic similarities in format and content. Data presented in Extensible Markup Language (XML) format or the geographic data type Keyhole Markup Language (KML) format are examples of semi-structured data. Figure 1 provides an example of an XML snippet showing the metadata for a given traffic alert.

<?xml version="1.0" encoding="UTF-8"?>

<ResultSet xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xmlns="urn:yahoo:maps" xsi:schemaLocation="urn:yahoo:maps
http://api.local.yahoo.com/MapsService/V1/TrafficDataResponse.xsd"><LastUpdat
eDate>1262722386</LastUpdateDate><Result type="incident"><Title>Closed, on
RT-440 SB at COMMUNIPAW AVE</Title><Description>ROAD CLOSED; DUE TO
WATERMAIN BREAK REPAIRS FOLLOW POLICE DETOURS ALSO THE RAMP TO
SOUTHBOUND 440 FROM COMMUNIPAW AVENUE IS CLOSED AS WELL AS
NORTHBOUND TRUCK RT 19 TO RT 440 NOTE: DOT REPORTS THIS WILL REMAINS
CLOSED UNTIL FURTHER NOTICE. SEEK
ALTERNATE.</Description><Latitude>40.723743</Latitude><Longitude>-
74.090166</Longitude><Direction>SB</Direction><Severity>4</Severity><ReportD
ate>1262599901</ReportDate><UpdateDate>1262699951</UpdateDate><EndDate

Figure 1. Traffic alert using Really Simple Synchronization (RSS) messaging.

The above output is a semi-structured text message that the data collector would transfer to a mobile device to alert drivers to a water main break in the specified area. These data are embedded within a metadata processing language that is human readable but can only be fully visualized through a human-computer interface such as a Simple Message Service (SMS) reader. Figure 2 shows the visualization of this message as a GeoRSS feed using the Bing Map interface. Note how easily a reader can understand the impacted area thanks to the additional spatial context that results from showing the road network with easily identifiable roads and traffic avoidance areas. While the SMS translates the XML tags into a readable text message, the GeoRSS provides another dimension of detail in visualizing the output, placing the messaging service into a geographic context complete with a road network and geopolitical boundaries that identify the area in which the water main break occurred.

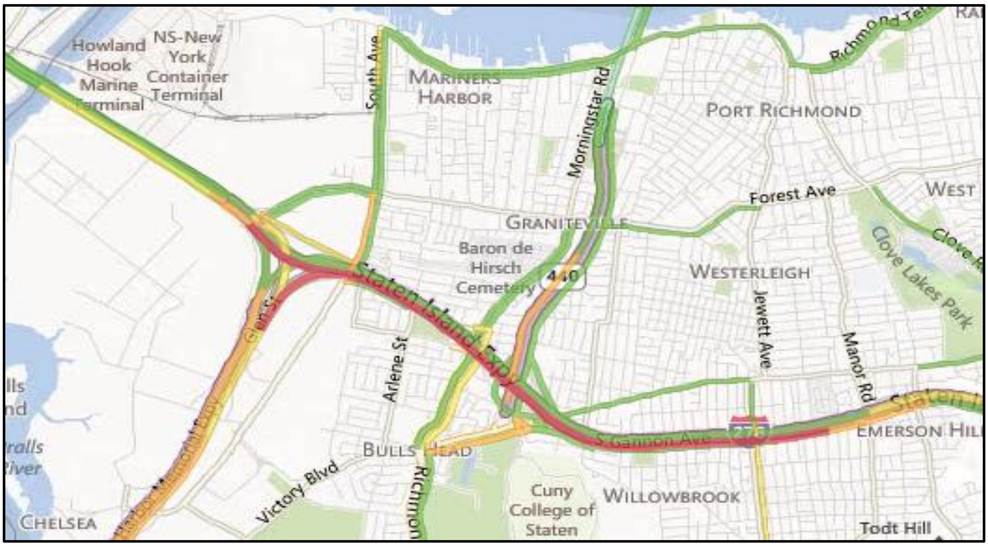


Figure 2. Above traffic alert visualized using GeoRSS in the Bing map interface. Adapted from Bing (2013).

2.3. Unstructured Data

Unstructured data encompasses the realm of data objects represented by the semi-natural, irregular language of social media, as represented in blogs, instant messaging, Facebook posts, Instagrams, tweets, among others. To leverage such data for sociocultural understanding, researchers need to capture the data and integrate them into an analytical methodology, which is antithetical to the very premise of unstructured data as a free-form collection that resists a priori hypotheses regarding its internal structure. This is the very challenge that now defines the realm of Big Data and its analysis. In essence, the difficulty centers on detecting the signal embedded within the noise, differentiating patterns of activities from outliers, and determining with some certainty that the patterns generated carry sociocultural meaning. Figure 3 gives a snapshot of unstructured data in the form of a Twitter feed from the Kenyan Ministry for the State of Defense during Kenya's war on the Al-Shabaab terrorist network in November 2011.

Figure 3. Tweet advising Kenyans not to sell animals to Al-Shabaab. Adapted from Twitter (2011), Maj. Chirchir Twitter feed.

This same Twitter account, however, posted manipulated images of an individual allegedly stoned by Al Shabaab militants in order to provoke nationalistic outrage within Kenya. Sentiment manipulation illustrates why researchers should approach these new media technologies with caution

Visualization of unstructured data requires new techniques to identify the relative importance of the various data elements. These data are not necessarily accessible to the traditional metrics of structured data. Figure 4 shows an example of visualizing the predominance of registered users among various social networking sites. In this visualization, font sizes scale to relative numbers of registered users. To read this graphic, consider the example of "facebook." This social media platform garners far greater numbers of registered users relative to the other media providers. This distinction is evident by the larger font size. In contrast, Studivz, a social media platform geared to university students in Central Europe, is referenced by a much smaller font size, indicating a smaller user base.

Figure 4. Relative preponderance of social media platforms, November 2012.

3.0. Organizing the Conceptual Framework for Visualizing Understanding

As outlined in the introduction, visualization can be conceptualized using three different, overlapping paradigms. Visualization of understanding as an interpretation of external form, as a discovery tool, and as an exploration of the internal cohesiveness of the visualized patterns lead researchers to use different data collection methods and formats to parameterize sociocultural interactions. A meta-discussion of the models and tools can increase understanding of inherent bias in the methodology employed to comprehend a particular social group or cultural practice. Clear benefits accrue from using visualizations appropriate to the particularities of the data scrutinized. We next describe some of the practicalities of visualizing sociocultural data through these frameworks and their use in representing the underlying sociocultural relationships. We examine the conceptual frameworks within the context of (a) linguistic networks of convergent ideas as manifested in group rhetoric, (b) affinity diagrams showing the organization of unstructured data, (c) conceptual mapping, and (d) link analysis of known social networks.

3.1. Linguistic Networks

Michael Gabbay and Ashley Thirkill-Mackelprang (2011) developed a deterministic framework for characterizing the various insurgent groups during the Iraq war (2003–2009). Their research distinguished among groups based upon the rhetoric the groups used and defined two broad categories of insurgents: the Jihadist Salafists and Nationalists. The Jihadist Salafists (for instance, Al Qaida in Iraq and Ansar al-Islam) adhere to a strict, orthodox interpretation of Islam and identify themselves with a pan-Islamic caliphate. The authors characterized these groups as unequivocally hostile to Shiites and to groups affiliated with the Iraqi government. In contrast, Nationalist groups in Iraq emphasize the geographic and ethnographic integrity of all Iraqi citizens and favor a central government espousing a basis in Islamic law. Nationalist groups express varying degrees of anti-Shiite sentiment, but overall their key rhetoric centered on maintaining a united Iraq for Shiites as well as other ethnic groups and sects within the country.

Gabbay and Thirkill-Mackelprang posit that rhetoric constitutes the central political observable of an insurgency because it delineates the degree to which an insurgent group tolerates and / or celebrates violence to meet its political objectives. The authors devised a series of “conflict frames” to leverage this unstructured data and identify in-groups (i.e., insurgent groups with similar political objectives and willingness to engage in violent acts) and out-groups (i.e., the U.S. military, its allies, Iraqi National Security Forces, and local groups willing to collaborate with U.S. forces). The unstructured data used in this study encompassed over 2,000 translated statements from 18 of the most vocal insurgent groups. Table 2 provides an example of the kinds of in- and out-groups that Gabbay and Thirkill-Mackelprang identified throughout the Iraq war as well as the various marker terms used to structure the degree of rhetorical violence with which these groups propagandized their respective causes.

Table 2. *Rhetorical marker terms and in- and out-group assignment.*

Marker Term	**In-Groups**	**Out-Groups**
agent government		Iraqi Government
apostate government	Sunni Civil Society	Iraqi Government
companions of the prophet	Sunni Civil Society	
cross worshippers	Sunni Civil Society	United States
Iraqis	Iraqi Civil Society	
Iranian occupations	Sunni Civil Society	Iraqi Government, Shiite Political Parties
Occupier		United States
Rejectionist	Sunni Civil Society	Shiite Civil Society
Rescue council		Sunni militias (Awakening Councils)

Note: Adapted with permission from Gabbay & Thirkill-Mackelprang (2011)

3.2. Context Inquiry and Affinity Diagrams

Context inquiry offers an excellent way to explore group dynamics and the individual's role within a group. In this approach the researcher meets with a subject for scheduled observational interviews during which time the subject continues his or her daily routines and interactions with other members of the community. Through observation and interviews, the researcher begins to understand and interpret the subject's actions as informed by and consequent to the larger group dynamics. Context inquiry offers the tactical advantage of affording subjects an opportunity to develop a narrative about their personal lives and the interrelationships informing the larger social context.

This kind of research produces structured or unstructured data, depending on whether the researcher collects measurable attributes (e.g., number of calories consumed per day, hours of sleep per night) or information derived from conversations (e.g., survey instruments, informal conversations). In either case, the framework for visualizing the interactions can take the form of a simple graph of daily calorie intake or hours performing specific tasks, a link chart of the social network and communications relay, or a detailed model of the subject's daily life as a micro expression of the larger social interactions defining the social and cultural norms. This type of inquiry tool is also amenable to scrutinizing the kinds of preconceived notions that informed the observer's understanding of the society prior to this intimate view at the personal level.

Researchers can use affinity diagrams to structure the visualization of data obtained from a context inquiry. To generate an affinity diagram, the researcher sorts various data snippets, whether expressions used to characterize an interaction, the flow of an interviewee's daily tasks, the hierarchical structure of civil institutions, etc., into groups based on their natural relationships. These groups may be further sorted into subgroups to better facilitate a logically coherent analysis of daily observations. The affinity diagram graphically conveys groupings and relationships. Figure 5 shows an example of a disordered set of observations structured into a hierarchical diagram that organizes thoughts and ideas for better understanding. Affinity diagrams are designed as brainstorming tools and as a free form collection of information snippets that can be easily moved from one category to another as new information is posted to the diagram or as the researcher reorganizes categories of the hierarchy.

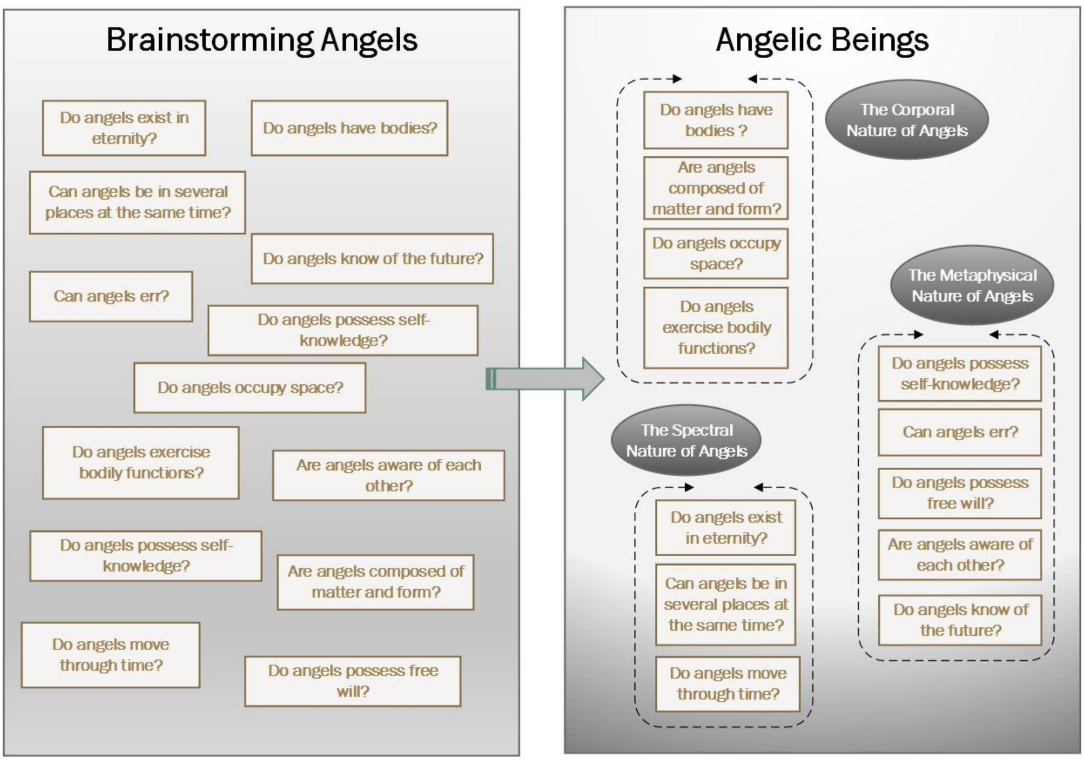


Figure 5. Affinity diagram structuring data elements into logical categories.

Context inquiry also affords the opportunity for subjects to self-reflect on previously unrecognized aspects of their daily lives, based upon interpretations offered by the researcher. Because affinity diagrams are designed to facilitate discussion, the researcher can gauge the accuracy of interpretations by the degree of validation offered by the subject to the derived categories or even the rationale used to organize data into a given category.

3.3. Concept Maps

Concept maps are two-dimensional graphic visualizations of knowledge concepts and the propositions that actively join concepts in one-to-one, one-to-many, or many-to-many entity relationships. They offer the flexibility of multiple relations occurring across one or many domains, which makes them ideal visualization tools. As framework tools for visualizing understanding, these maps facilitate an understanding of the external organization in which individuals interact, can help researchers to identify power relations within an organized structure such as a government entity or an institution, and can be used to comprehend the internal workings of a group acting within the larger social organization. Concept maps sketch the entities defining a domain of knowledge in such a manner that the more generalized concepts appear at the highest level of the map and the more specific concepts are arranged as subsequent linkages (Canas, Carff, Hill, Carvalho, Arguedas, Eskridge, & Carvajal, 2005).

Concept maps become tools for building an understanding of other cultures because each manifestation of relationships and the propositions joining them bears the unique perspective of the individual researcher or, in the case of a context inquiry, of the researcher and subject. As theoretical frameworks, they have the interesting attribute that no two maps are identical because they directly reflect the level of expertise, domain knowledge, and linkages that the user brings to their construction. As an example, a new laboratory assistant will have a very limited understanding of the hierarchical structure of the entire research program, whereas a seasoned researcher will better understand the interworking of the organization and will have substantial contacts with external organizations upon which the research program relies for its funding. These two individuals would generate two vastly differing concept maps: one limited to the more salient aspects of the research work as a whole, and the other a more abstract representation of the program as but one element in a much larger, interconnected network of research organizations and funding operations. Thus, a concept map is very much an individual endeavor, with many different representations of the interactions and interconnections surrounding a knowledge domain.

3.4. Network Linkage Analysis

Link analysis represents relationships among entities within a specified network or within a platform, such as Web search engines, site visits, or telecommunication networks. Law enforcement makes extensive use of link analysis to locate known suspects or terrorists, whereas financial organizations use link analysis to track possible fraudulent account transactions. Development of link analysis tools is fast becoming a mainstay for data analysts who use these tools to mine for relationships that are purposely nonlinear so to mask direct connectivity. Figure 6 shows an example of a link analysis concerning a bank officer who makes several loans to customers with multiple fraud alerts tied to their respective bank accounts. The left side of the figure shows the network linkage diagram that identifies those accounts with alerts flagging fraudulent activities. The right side of the figure zooms in on one individual (or nodal point) within the network and his relationships to these fraudulent accounts. Other uses of link analysis include monitoring cyber security, mapping disease outbreaks, and performing research on the potentials of new markets.

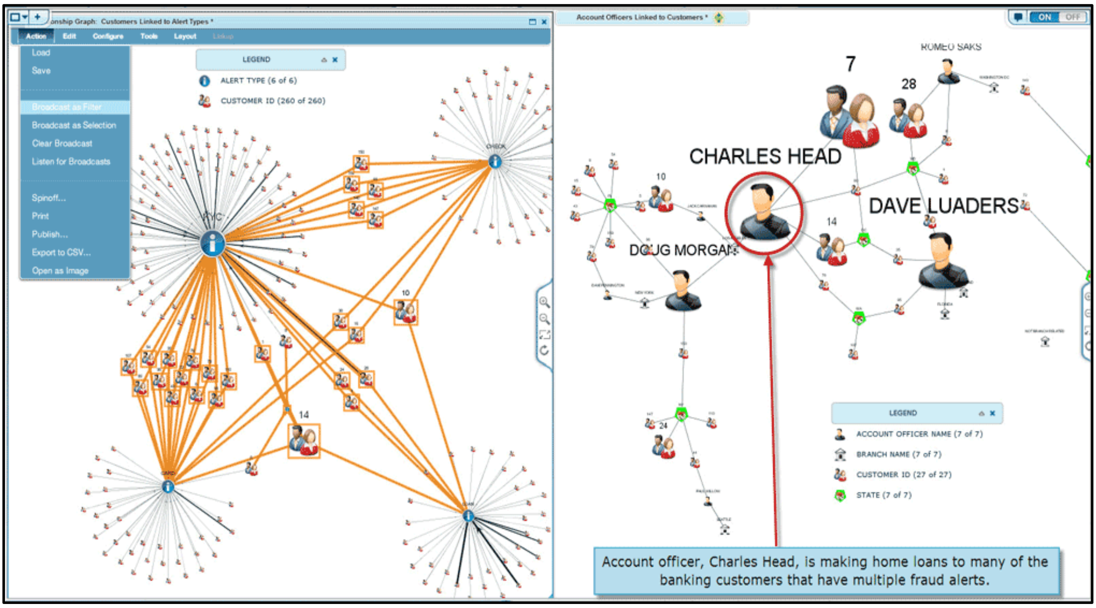


Figure 6. Network linkage analysis of fraudulent transactions. Image created using Centrifuge Systems Analytics (2012) tool.

Researchers use link analysis to identify central nodes within a network and to model the interactions of those nodes across networks. Link analysis is also very useful for recognizing patterns and trends within a social network, and permits mapping of individuals and their relationships within a specific time window or a defined geography. As a visualization framework, link analysis lends itself to discovery of substructures within the larger networked environment and allows an elaborate conceptual mapping of the hierarchy through which nodal points interface. The linkages from node to node or across domains can be defined based upon a particular activity or to track an individual and their contacts to any number of degrees from the originating node.

4. Visualizing Quantifiable Data

In developing the techniques and tools for visualizing social interactions and understanding the underlying processes, researchers begin with the onerous task of selecting the data necessary to achieve the stated objective. The advent of affordable, readily available, high-capacity computer systems and the accompanying software for data processing has made the volumes of data collected in recent years truly staggering. In concert with affordable, high-capacity computing, data analytics has enjoyed a surge of capabilities brought on by data mining algorithms, self-organized mappings, and multi-dimensional visualizations.

Visualization of these vast quantifiable datasets encompasses a broad epistemological practice categorized into three discrete actions: looking, querying, and questioning (Dodge, McDerby & Turner, 2008). Each of these requires the researcher to select and define the domain of interest in which to visualize the interactions among entities. Using a multiplicity of graphic representations to

address these epistemological practices has great value, since it produces multiple viewpoints of the underlying data relationships. Seeing data presented in many different perspectives provides context and aids the researcher in determining the variables best suited for representing complex social engagements.

4.1. Looking, Querying, and Questioning

Looking, querying, and questioning are unique components of understanding that allow us to conceptualize the interrelated and sequential elements of the visualization process. These three actions facilitate the development of larger constructs of sensemaking around which actors engage. In the process of understanding the cultural and social context of a given set of social interactions, researchers select, whether consciously or not, what they perceive to be the most relevant attributes of those interactions and create visualizations that best portray how actors engaged in these social interactions are constrained and / or contextualized.

Looking involves the observation of an object of interest. The observer begins the visualization process by presenting graphic depictions of an object. Looking entails simply defining an inquiry through visualization or as a more elaborate activity in which the observer defines the constraints for observation (e.g., time of observation, duration of observation, scale of observation), the area of interest in which the observation is conducted, and any signals that would mark a change within the object under investigation.

Querying establishes which data elements have particular significance for understanding a social dynamic or cultural practice. Queries about these elements serve as the direct interface that a researcher deploys in assessing an event or interaction. Querying is a form of classification that introduces a wide range of capabilities and limitations on direct observation. By placing data in pre-existing categories, researchers open themselves to the criticism of bias and selective visualizations that often present prejudicial views of the actors being investigated. Likewise, a poorly constructed query can introduce limitations with respect to the data extracted for the visualization. Poorly constructed queries that are too constrictive of the available data do not necessarily indicate a lack of robustness within the available data but rather are more indicative of a lack of understanding as to how the query is structured and how the data were collected.

Questioning defines the very nature of the investigation. It combines the visual insight rendered through looking with the analytic results of querying to explain the observed phenomenon. Questioning represents the culmination of the looking and querying processes. Questions articulate the discovery process.

Interfaces embedded in Web applications serve as ideal representations of the visualization process as a looking, querying, and questioning experience. From initializing the domain of interest, to structuring the querying capabilities of the domain, to finalizing the visualization and asking the relevant why, what, and how questions, Web-based applications have proven invaluable tools for researchers culling a multitude of data sources. Using a Web application interface as the example of looking, querying, and questioning allows the observer to examine output in dynamic, multi-formatted views. Figure 7 is a screenshot taken from the Spotfire Decision Support System, an

interactive data analysis and visualization platform. The graphic provides a demographic snapshot of natality rates in Washington, D.C., showing percentage pie charts by gender, histograms by race and ethnicity, and a regression analysis of age of mother vs. age of father.

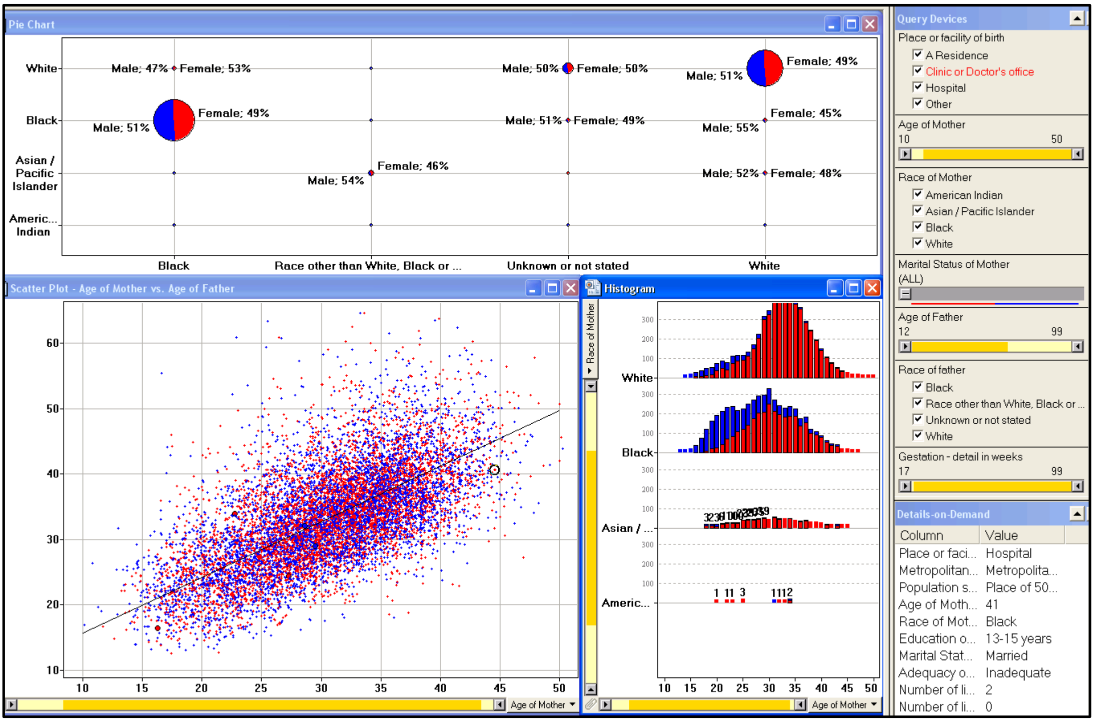


Figure 7. Natality data for the District of Columbia as visualized from a Web-based database application. Adapted with permission from Shneiderman (2013).

In Figure 7, the multiplicity of views provides an overarching construct that helps researchers to investigate natality rates for the city. By exploring parental characteristics such as racial composition, age, or marital status, researchers can correlate multiple factors influencing natality rates using a multi-view interface. For example, in the above figure, the age relationship histograms show that offspring of younger Black mothers in Washington, D.C., are more likely to have older fathers than the offspring of White, Asian, or Native American women. To further explore this pattern, a researcher could click on the histogram of Age of Black Mothers and Age of Black Fathers to highlight those data points within the scatterplot regression view and show the variability of the distribution against a normalized regression. Such visualization can be further explored by examining the highlighted pie charts of the age relationships by racial groups to further investigate the relationship between age of parents and race of parents.

Questioning structured hierarchical relationships represents an important knowledge discovery technique and can be used to explore the underlying taxonomy of the data. A multi-view interface allows researchers to alter the classification schemes so as to emphasize particular relationships

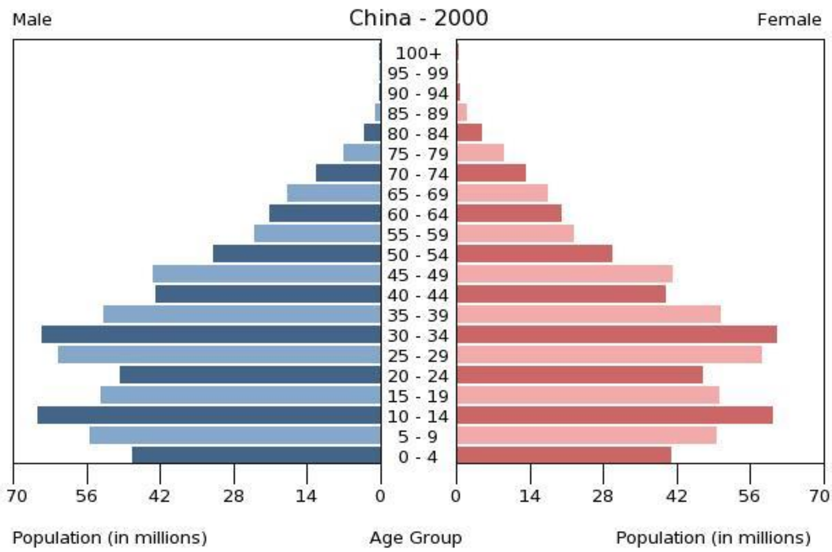
considered more significant than others, while also providing additional views of the data for further analysis and hypothesis testing.

4.2. Graphical Methods of Visualizing Understanding

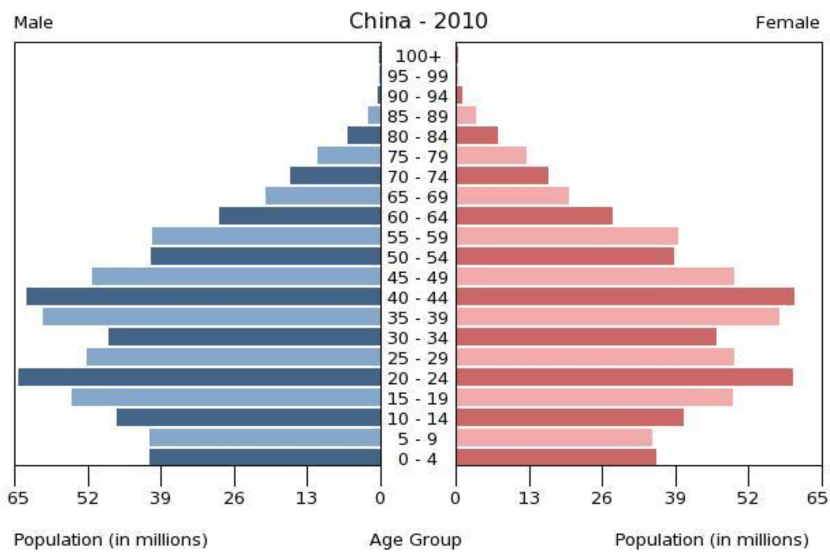
Before delving into the more sophisticated techniques of visualizing social dynamics and their complex interactions, we first consider the traditional methods of visualizing metrics of the social organization itself. These include common graphic layouts of variables in such forms as bar charts, scatterplots, histograms, and pie charts. Traditional data visualizations such as these allow an initial glimpse into the underlying workings of organizations, social systems, and the actors engaged within those relations.

Charts present useful graphic displays of single or multivariate data using simple *x*- and *y*-axes or multidimensional axes for variables whose distance measures depend upon the *x* and *y* variables. Data can be organized as nominal, ordinal, interval, or ratio. Charts can display measurements of selected variables as count values, average values, minimum and maximum values, median values, or outliers. Each variable conveys a different perspective on the information visualized. Continuous measurements are useful in comparing fluctuations across a spatial or temporal domain, identifying correlations, understanding trends, and—when viewed at multiple scales—gaining a holistic perspective of interactions between variables. Discrete measures can be visualized as categories of names, rankings, or scalars.

Figure 8 displays population pyramids from the Chinese census from 2000 through 2030. A population pyramid amalgamates census data and visualizes it based upon two or more variables. The four population pyramids (Figures 8a through 8d) show the age shifts by gender beginning with the 2000 census and segmented at 5-year increments. In each of these graphs, the population distribution begins with the youngest group (0–4 years of age) and extends to 100+ years of age. In the 2000 and 2010 population pyramids (Figures 8a and 8b), males outnumber females in the age categories 0–14. In each of the graphs, 10-year increments are demarcated with a darker bar than the off-decade age groups. For both census population pyramids, the ratio of males and females remains equal until the 70-and-above groupings. The projected 2020 population pyramid (Figure 8c) is the only one to show a larger proportion of the population in the youngest age groups as being predominantly female. Females outnumber males in the age groups 0–24; the proportions become equal at 25 and show a slight majority of males in the 60–70 range. In the projected population composition for 2030 (Figure 8d), the ratio of males to females increases dramatically in the ranges from 0 to 40 years, with females only representing a majority of the overall population for ages 60 and above.

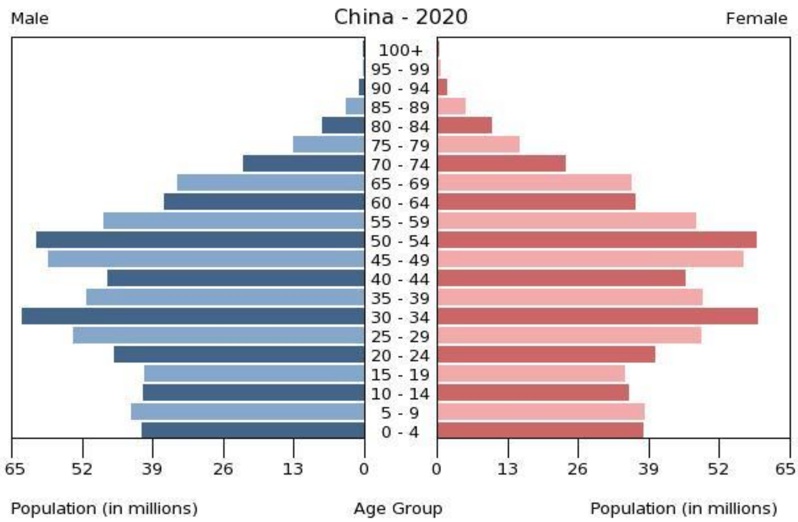


(8a)



(8b)

*Figure 8a & 8b***.** Population pyramids of China, 2000–2030 (estimated) by age groups. Adapted from the U.S. Census Bureau (2013), International Census Database.



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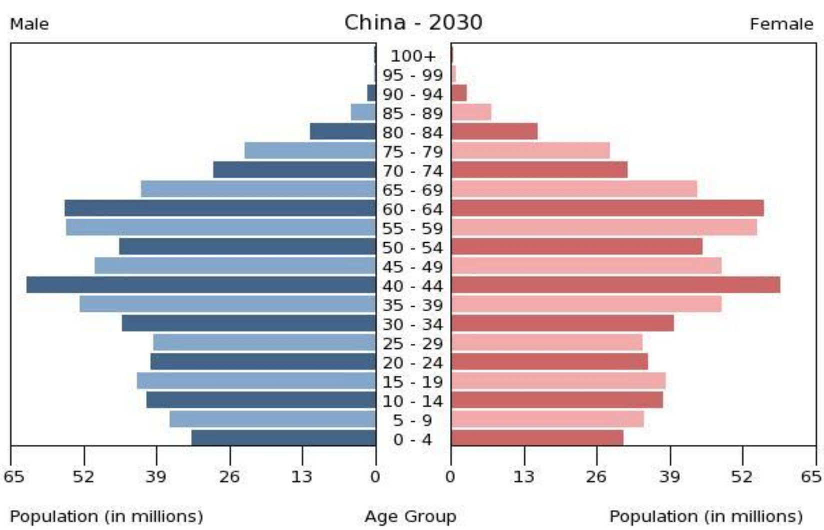

(8d)

Figure 8c & 8d. Population pyramids of China, 2000–2030 (estimated) by age groups. Adapted from the U.S. Census Bureau (2013), International Census Database.

Understanding the demographic composition of a population affords the researcher an overview of the constitutive requirements of resource allocation for that society (Ebenstein, 2010). The age composition of a population helps to explain allocation of food and medical care (Marks, Cargo, & Daniel, 2006). The racial, ethnic, and gender composition of a society also provides insights into the potential for cooperation or tensions within the social network (Wilson & Taub, 2007). All of these driving forces of the social environment can be appreciated and understood through the precursor of the demographic composition that characterizes the society at large.

Conveying multiple dimensions of information through visualization often entails juxtaposition of context to further illustrate the graphic visualizations. Figure 9 shows the global distribution of private wealth from 2009 to the estimated holdings for 2016. The bar graphs in the figure are divided into specific regions of the world based on geopolitical boundaries and show wealth in dollars across all private households. The callouts above each year's bar graph indicate the percent change in total private wealth based on complete numbers and aggregated to the countries within each defined region. Upon initial inspection, this graphic shows that private wealth in North America, Western Europe, and Japan decreased from 2010 to 2011, whereas over the same period private wealth increased in all the other regions identified. The inset at the bottom right of the graphic shows that despite the decline in private personal wealth among the wealthiest nations of North America, Western Europe, and Japan, the overall wealth of private households increases steadily for each year within the study (2009 through 2016 estimated).

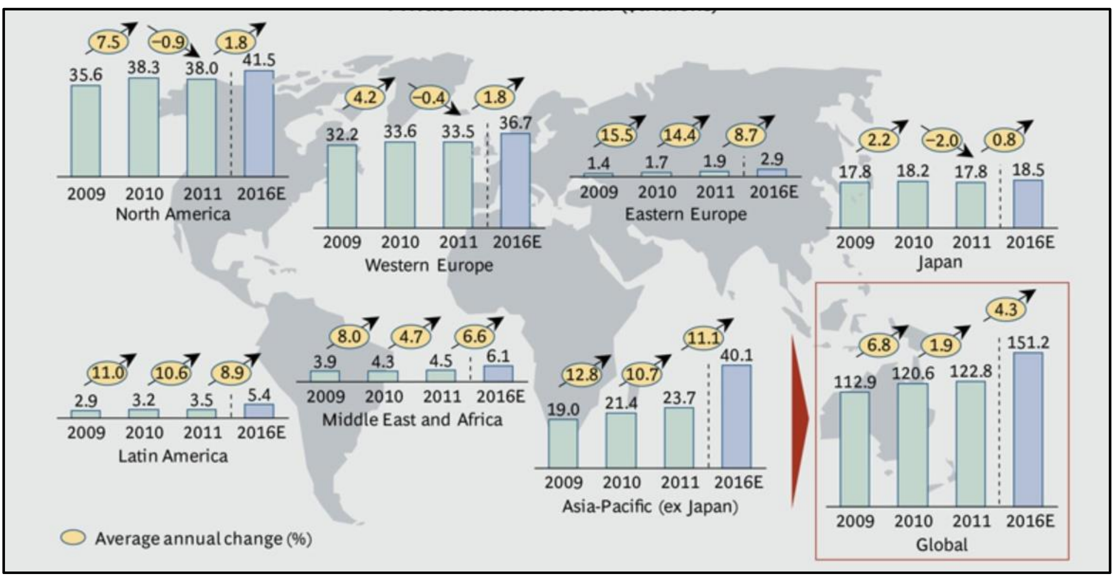

Figure 9. Growth of global private wealth, 2009 to 2016 (estimated). Adapted with permission from the Boston Consulting Group (2012), BCG Global Wealth Market Sizing Database 2012.

Tree diagrams (dendrograms) offer another useful way to visualize hierarchical relationships logically organized along specific paths. In Figure 10, a tree diagram shows a logical partitioning of the "Old World" (i.e., North America, Western Europe, and Japan), which registered negative growth of private wealth from 2010 through 2011, from that of the "New World" (i.e., Asia-Pacific, Eastern Europe, Latin America, the Middle East, and Africa), which experienced significant increases in private wealth during the same period. The arrangement of the tree diagram gives insight into the wealth distribution clustered around those regions that showed the greatest increase in private wealth against those regions with the greatest decrease. This arbitrary delineation enables researchers to explore the factors contributing to the "Old World's" advances and declines in private wealth to those increases and losses occurring in the "New World."

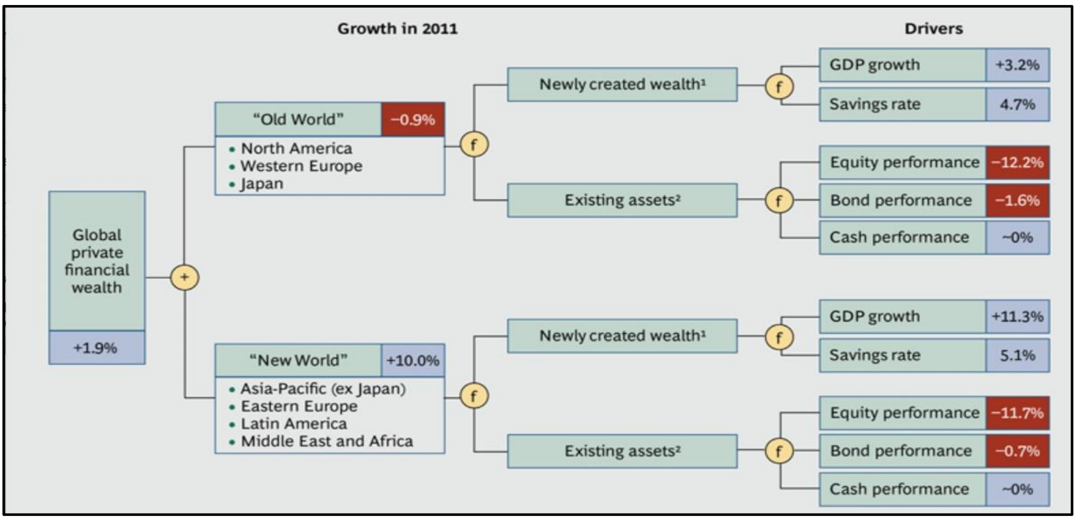

Figure 10. Global Growth of "Old World" and "New World" Private Financial Wealth. Adapted with permission from the Boston Consulting Group (2012), BCG Global Wealth Market Sizing Database 2012.

Reading a dendrogram entails following the path from one level of the hierarchy to the next. Tree diagrams have particular value in furthering understanding of complex, multidimensional occurrences because they branch from a known state into unique and separate states derived from their original point of departure. Intelligence analysts must entertain multiple, often contradictory, theories regarding event scenarios in order to eliminate hypotheses based on potential outcomes derived from uncertain inputs, and therefore find dendrograms particularly useful.

5. Visualizing Understanding in Multi-Dimensional Space

Computer-based display capabilities make the interactions among social actors more accessible by presenting a dynamic, multidimensional perspective. Social media and interactive hardware and

software open data exploration to a diverse range of unstructured data that are relevant at multiple scales of interactions. Because social media generate a “grab bag” of unstructured data streams, any traditional variable of interest in the social sciences can be equated to its representation as a lumped parameter within social media. In other words, some amalgamation of social media data can visualize complex concepts such as the political, economic, public health, or demographic composition of a community. Similarly, interactive media can embed the observer in controlled interactions to explore hypotheses about engagement and create more fruitful situational awareness.

5.1. Interpreting Social Media

Social network analysis studies relationships among actors in a community or group. While the technology of social networking is new, and the human-computer interfaces of social networks continue to evolve, the messaging and social structures reified in this technology are of keen interest to the social and behavioral sciences for the same reasons that one-on-one interviews remain a relevant data collection method: human interactions are complex and multidimensional, and are based upon social organizations and cultural practices. The virtual space offered through social media is the quintessential multidimensional space. Social media allows users to interact with individuals across the globe, engage in activities that span the gamut of interests, and allow one to assume an identity consummate with one’s personal interests.

Social network analysis came into its own in the 1960s. The process is built on network graph theory, in which complex interactions are visualized as networks. Network graph theory visualizes connections using a standard set of tools that include nodes represented as circles or ovals and linkages represented as arrows. The relative size and shape of a node or vertex indicate the node’s or vertex’s prominence within the network. The lines linking vertices represent directed or undirected linkages, depending upon how individual entities relate to each other within the network. A directed link indicates a reciprocal relationship; for example, the way “friends” link to each other in the Facebook network. An undirected link represents a user following another user, however, an undirected link relationship is not necessarily reciprocal. For example, a Twitter user may follow a very popular Twitter account, such as that held by a celebrity or politician, but need not engage with the account owner to be part of that network.

Social networks are of great interest to social scientists because the structure of the network visualization provides information about the activity surrounding particular nodes, not just about the nodal point itself. The density of arrows to a particular node indicates the popularity, or prominence, of an entity within the network. Shorter, more densely drawn arrows indicate relationships between nodes that entail significant bi-directional traffic. Networks emerge, gain prominence, motivate actions, and / or influence events. A research area that will prove significant is to chart the ecosystem of a social network, e.g., how does an influential social network emerge? What are the characteristics informing its expansion? What impacts does a social network have on its members? How does a social network continue to foster relevance or, consequently, what are the determining factors in its decline?

5.2. Online Social Networks

Online social networks include email networks, discussion boards, threaded conversation networks, Twitter, Facebook, YouTube, Flickr, and the ever-expanding hyperlink networks of the World Wide Web (WWW). These networks connect disparate groups through the confluence of influential contributors, timely topics, and interests in furthering a particular cause. Online communities emerge through any number of configurations constructed on the basis of political, social, economic, ethnic, religious, or other impulses. Figures 11a and 11b show Smith's (2013) comparative analysis of the social network that emerged during the "Occupy Wall Street" protests using a snapshot of Twitter tweets on November 15, 2011, and network traffic on the same day among Tea Party adherents. The respective networks are grouped by their affinities and show undirected links, or "replied to," "mention," or "follow," to either "occupywallstreet" or "teaparty." Replies and mentions stream across various groups within each network.

Of particular interest in contrasting these networks is that at the time of Occupy Wall Street's greatest momentum in November 2011, the majority of network traffic involved replies and mentions, whereas in the Tea Party network the majority of traffic flowing among the affiliated nodes involved following particular accounts, with far less direct engagement of isolated users. An observer noting the characteristics of these respective networks would conclude the cohesiveness of Occupy Wall Street to be far more entrenched than those of their Tea Party counterparts. Yet, the organizational staying power of the Tea Party network suggests that while the community interactions of Occupy Wall Street were more densely construed, the adherence to the social message of a few influential members of the Tea Party network is able to reverberate throughout the social fabric and remain a relevant part of the political discourse.

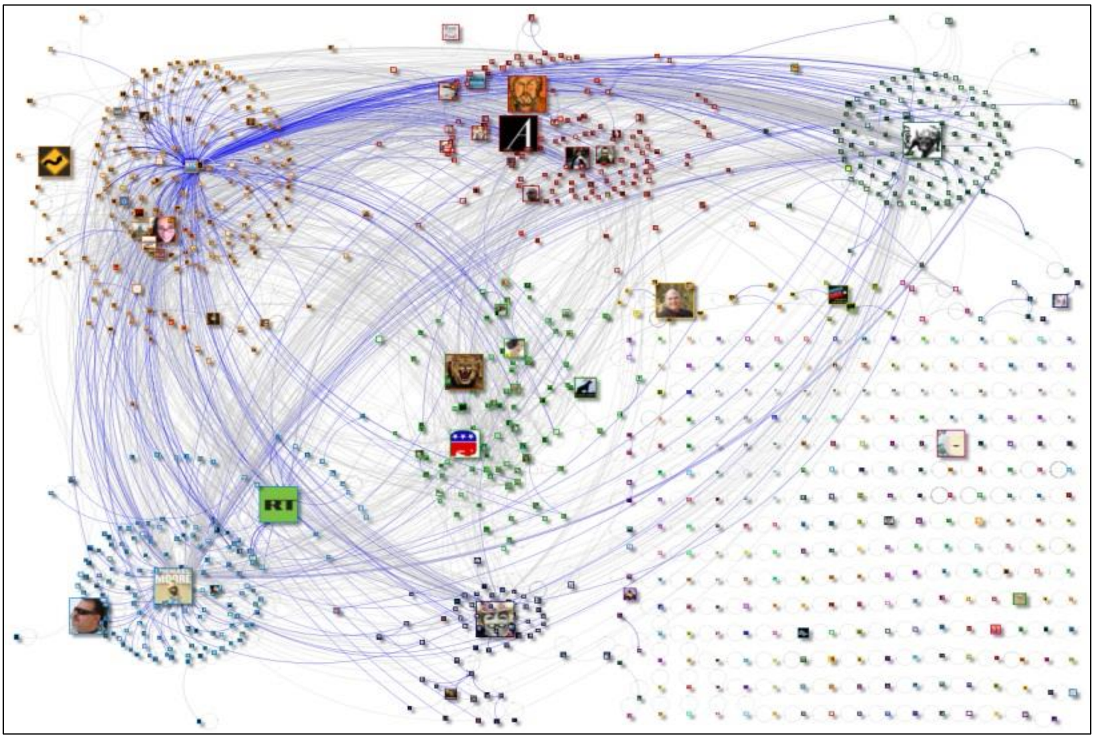

Figure 11a. Social network comparison of Occupy Wall Street and Tea Party – Occupy Wall Street network. Adapted with permission from The Social Media Research Foundation (2012), NodeXL Network Graphs.

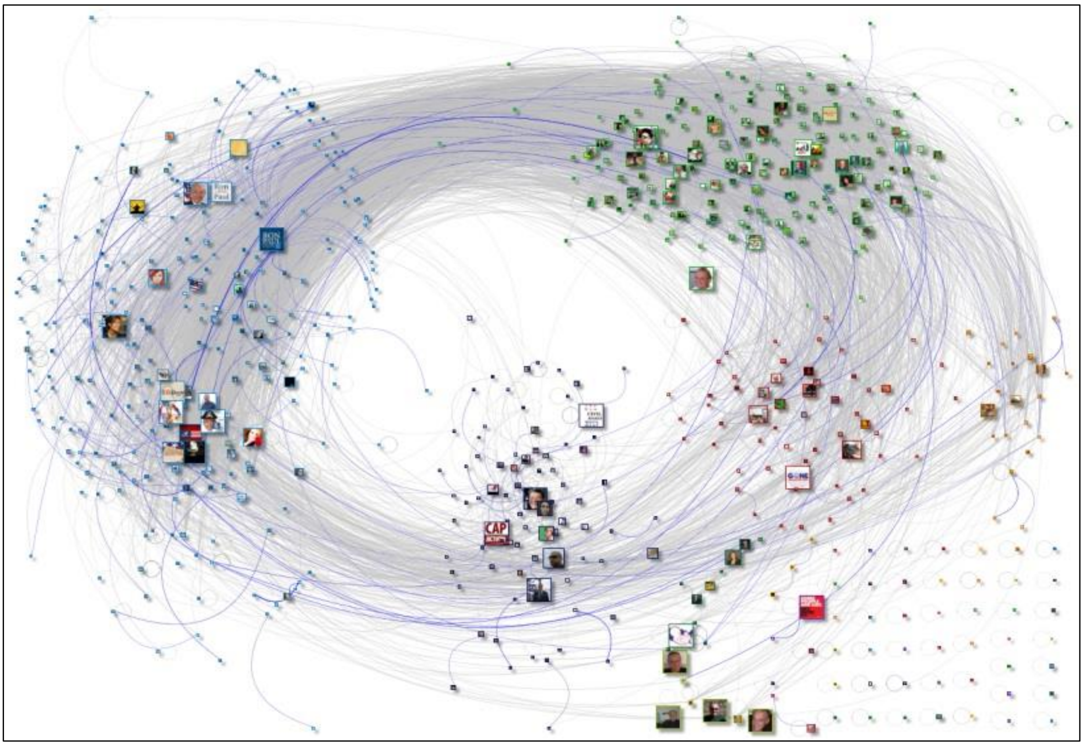

Figure 11b. Social network comparison of Occupy Wall Street and Tea Party – Tea Party network. Adapted with permission from The Social Media Research Foundation (2012), NodeXL Network Graphs.

During the height of media attention focused on Occupy Wall Street, the network comparisons suggested Occupy Wall Street had a greater community footprint than the Tea Party. However, a social researcher may be particularly interested in the long-term configurations of these respective social networks as they experience vastly different political lifecycles.

Social networking sites such as Facebook and Twitter have millions of subscribers who post daily updates regarding their personal activities, relationship connections, and general interests. This information is available to members of each participant's personal network. Social communities exist within the confines of these social networking platforms. These communities can openly express the ideas that encompass their notion of community or can be more secretive and actively mask their community's underlying objectives. Social communities that use network sites to grow and to propagate their ideas supply intelligence analysts with a wealth of information on the topics that define or directly impact their community.

Social network analysis tools are evolving to include sophisticated linguistic analysis of sentiment conveyed in the messages that comprise the overwhelming traffic on social networking sites. While the inclusion of linguistic analysis of social media is a new venue in social research, it promises a tremendous value in assessing the state of a given community and how they perceive their

interactions among themselves and with other groups. In the following sections we explore two social media analysis tools used to assist intelligence analysts in understanding the sentiment surrounding a topic or event: Tweet Explorer using Linguistic Inquiry and Word Count (LIWC) and Sentimedir.

5.2.1. Tweet Explorer/ Linguistic Inquiry and Word Count

The MITRE Corporation developed Tweet Explorer as a high level integration tool that tracks the general mood of Twitter users and their interests in domestic and international social and cultural events. Analysts query tweets based on semantic parameters, including hash tags, keywords, locations, and dates. Tweet Explorer then sorts key words identified within the tweets using indicator words defined by the LIWC dictionary. Indicator words connote emotional state, such as satisfaction, anger, happiness, etc.

Tweet Explorer visualizes trends in the mood reflected in the extracted tweets by mapping levels of emotions expressed across a timeline and allowing users to discover the times at which levels of emotions shifted significantly into a higher or lower phase. Once these 'breakpoints' in time have been identified, users can examine them against events that unfolded on the ground at those times. In this way, users can gain insight into the emotions people expressed while certain events occurred. After isolating a set of tweets, the analyst can view the actual text of the tweet for further consideration.

In Figure 12, a timeline represents the results of a query coincident with the pending national election in Kenya. This example shows the time period January 23, 2012 to July 2, 2012. During this time, the political leaders in Kenya and much of the international community braced themselves for potential outbreaks of tribal-induced violence reminiscent of the aftermath of the national elections in 2007. The scatter plot shows levels of anger expressed in tweets referring to the national elections and the various political parties. Note the sharp increase around January 23. During this time, the International Criminal Court formally charged Deputy Prime Minister and presidential candidate Uhuru Kenyatta along with member of Parliament William Ruto of crimes against humanity. Subsequent outbursts of anger appear at the end of April 2012, which coincides with a church bombing in Nairobi.

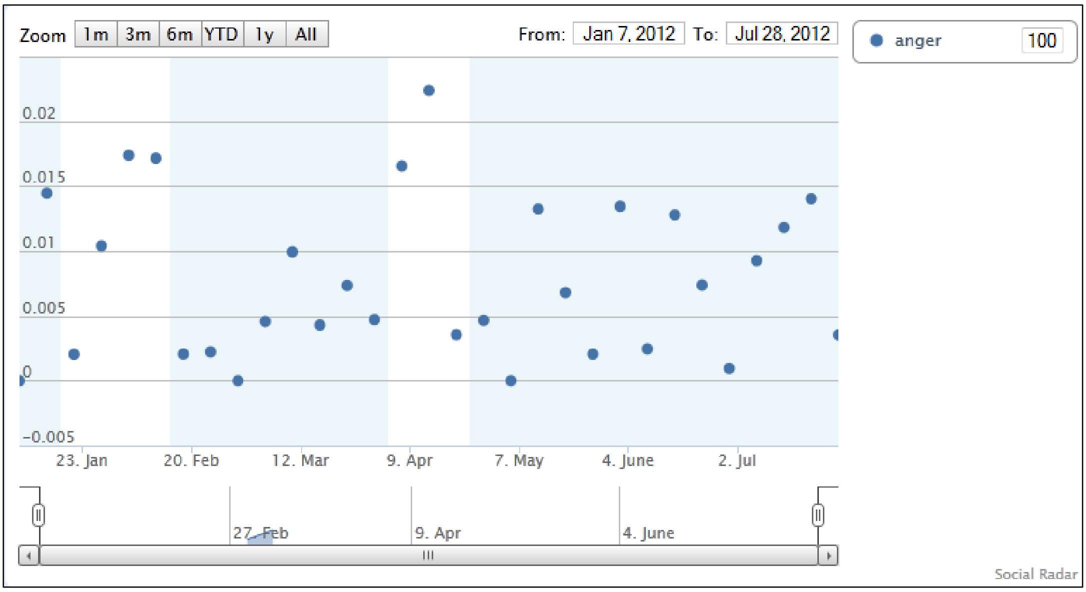

Figure 12. Tweet Explorer output of anger sentiments in Kenya, January to July 2012. Adapted with permission from the MITRE Corporation (2012), Social Radar Research Group.

5.2.2. Sentimedir

As social media proliferate and transition from personal chat forums and community share sites to principal sources of information and commentary on cultural events happening “in the street,” decision makers, be they city planners soliciting feedback on proposed biking lanes in a metropolitan area or marketing experts seeking to identify the next big thing, recognize these new media formats as potential gauges of how sentiments within groups unfold in near-real time. By isolating the preponderance of targeted words and phrases conveying emotions associated with a given topic and the behavior of individuals in response to events of interest, social media has the potential to revolutionize how groups respond to and interact as events unfold. This approach to social engagement analysis focuses on the language used, the cathartic impulses conveyed and the impact of coordinated responses as exposed in the social messages that proliferate.

The MITRE Corporation developed a prototype tool—Sentimedir—to help gauge the operational value of sentiment analysis. Sentimedir ingests text, primarily from Web-based sources, including news and social media. It applies natural language processing (NLP) techniques to exploit semantic, lexical, and syntactic features in order to automatically detect expressed sentiment across millions of documents. System users can apply complex Boolean combinations of free text queries and structured filters against this processed data store to help illuminate the preponderance and dynamics of sentiment relative to many different features of the messages, including publication source, country, topic, date or even individual authors or detected opinion holders. Users may then visualize aggregate results in a variety of ways, including a daily index of overall sentiment, presented as a moving average with discrete indicators signaling when a change

in the index is statistically significant (Day, Boiney, Brown, Quimby, & Ubaldino, 2010). Other visualizations include stacked bar charts of the volume of positive and negative sentiment relative to these same kinds of metadata features, and pie charts, histograms and "word clouds" to display the various absolute and relative quantities of these different kinds of phenomena. In effect, this is a sentiment sensor capable of detecting, measuring, and contextualizing the extent to which a sentiment is shared within a group of users. The Sentimedir prototype is one of many research and development efforts underway to test the broad hypothesis that applied sentiment analysis technology can be an effective tool for visualizing and analyzing social engagement.

5.3. Virtual Reality Visualizations

Visualization techniques that move beyond two- or three-dimensional graphic representations to more interactive, immersive, multidimensional analytic space further aid understanding of the social dynamics of individual and group behaviors across cultural and social domains. Software packages have not only advanced functional capabilities for modeling complex social interactions but can also immerse the observer in high fidelity virtual realities that simulate the actual environment of interest. In addition, advances in hardware have significantly increased the degree to which observers can embed themselves in a scene, which provides an unencumbered sense of interaction. These immersive technologies can potentially allow users to play out a multiplicity of scenarios based upon research conducted on the ground with individuals from the social and cultural groups of interest, as discussed in the previous sections.

5.3.1. Surrogate travel

Surrogate travel combines the display of discrete variables underlying the foundation of the "scene" with interactive, multimedia simulations of an observer's experience of the created environment. It integrates observer participation into the sensemaking process, but does not immerse the observers in a virtual environment; a significant distance remains between the observers and the environment in which they are engaged. Surrogate travel can take the form of simulated flight panels, video cameras providing live feeds of a cruise ship or traffic flow, or even a live-camera feed of animals at the zoo that allows observers to check on the newest additions to the institution.

Flight simulators offer excellent examples of surrogate travel. The more recent simulators combine visual effects, sound effects, air-to-ground communication, and full body motion as part of the experience a pilot would anticipate in a cockpit. The simulated cockpit moves in the direction of the turns executed by the pilot at the control panel, and the throttle, rudders, and yoke exert a counterforce on the system. The plane's movements modulate the simulation of the terrain that the aircraft traverses as a function of increasing or decreasing altitude. While the plane is in simulated motion, pixelated views of the landscape alter as a function of the plane's threshold with respect to the radiance angle, while landscape shadowing reflects the zenith angle of the sun's rays based on the specific times of day programmed into the simulation. Engines and instrumentation sounds are integrated into the simulation, as are the communication relays with the air traffic control tower. This type of simulation familiarizes pilots with the way controls respond to their input and with the terrain through which they will fly, and helps them appreciate the sound patterns within the cockpit and the communication relays they will use.

5.3.2. Semi-immersive animation environments

Virtual reality modeling languages (VRMLs) (Cartwright, 2008) enable the technical development of semi-immersive and fully immersive animation. In these virtual worlds, the user adopts an online presence, or avatar, who becomes their persona in any number of virtual environments. Second Life, the online immersive space, is an example of a virtual world in which users create their living environments, establish relationships with other avatars, and generate a fully functioning second, virtual world. King and Fouts (2009) used Second Life as a segue into understanding the cultural practice of ijtihad[2] in the larger context of understanding Islam from a Western perspective. In their virtual journey to the Hajj in Mecca, the two investigators encountered Muslims from around the world with whom they were able to pose questions regarding Islamic culture and practices. By developing their avatars, the researchers were able to adopt the traditional dress and ornaments of the Hajj and gain a better understanding of what this ritual means to practitioners around the world.

Semi-immersive animation is used at the University of Southern California (USC) Institute for Creative Technologies (ICT) to create a training theater in which troops can simulate direct interactions with villagers, patrol streets known to be populated with snipers, and experience the chaotic engagement of a simulated street battle that includes the sounds of enemy fire, shockwaves from Improvised Explosive Devices (IEDs), and the deafening sounds of helicopters hovering above the battlefield. In preparation for strategic missions, virtual reality is used to prepare personnel for deployments into unfamiliar terrain. Virtual reality simulations of combat actions help train troops about battlefield conditions and better familiarize them with the pace of engagement and the confusing interactions inherent in actual combat (Vasquez, 2008).

Figure 13 is an example of this new kind of training environment known to researchers at ICT as FlatWorld. FlatWorld exposes combat troops to the look and feel of an Afghan village. In FlatWorld, all aspects of a battle are virtualized, including the helicopter flying overhead, which actually triggers shockwaves through the enclosure's floor when passing through the scene. Scents can also be added to the environment to simulate the smell of gunpowder, diesel fuel, and even the vegetables and flowers from the produce stall across the street. While this technology advances real-time simulation of battle conditions, the experience is not fully immersive because the observers remain outside the scene, and colleagues or subject matter experts, also outside the theater's enclosure, direct them on how to adjust their responses to the unfolding scenario.

[2] Ijtihad is the practice of independent interpretation of Islamic law (Sharia) based upon a methodic reasoning of legal precedence and couched in a practiced understanding of Islamic theology, a scholarly appreciation of the Quran, the traditional stories of the Prophet's life (Hadith), and scholastic consensus (ijma). For further discussion of Ijtihad see Gesink (2003).

Figure 13. Semi-immersive training scenario for combat in an Afghan village. Adapted with permission from the Institute for Creative Technologies (2007).

5.3.3. Fully immersive animation environments

Visualization of virtual environments is not constrained to simulation on a computer monitor. Many military and academic research centers have developed virtual environment tools that fully envelop the subject in a virtual reality experience.

Full immersion animation can be realized as an entire room designed as a high-resolution, multi-sensory simulation theater capturing user interactions through real-time scenarios. Researchers at the University of Illinois at Chicago designed and built the Cave Automatic Virtual Environment (CAVE), which consists of a room-sized 3-D video and surround-sound audio system with graphics projected on three walls and the floor (Kenyon, 1995). Users interact with the technology by wearing a location sensor and stereo vision googles. The location sensor signals to the 3-D video and audio playback to adjust viewing perspective and stereo projection relative to the user's location in real-time while the stereo vision googles allow the user to experience the 3-dimensional visualization at close range. The CAVE is designed for scientific visualization and has been used to visualize such disparate events as simulating displacements along a geologic fault plane or the buildup and dispersion of a water wave within a confined basin. Entire virtual ecosystems can be visualized using a fully immersive environment as evidenced by the burst of film projects utilizing 3-D technology to animate these interactive virtual terrains.

6. Visualizing Understanding Using Big Data Analytics

"Big data" is a term of art that includes both the processing of massive data stores and the technological advances that in-memory data systems and storage capabilities require to fully ingest, process, and analyze vast data streams. LeHong and Fenn (2012) refer to big data as a three-dimensional problem: increasing volumes of data (several terabytes to petabytes of data); the speed with which the data must be collected, processed, and delivered; and the multiplicity of data formats. This is known as the "3Vs" model: volume, velocity, and variety. While new data sources and modeling techniques offer greater possibilities for visualization and understanding, these same sources and techniques expose the researcher to new challenges that call for new ways of conceptualizing analysis and visualization, as well as the need for tools to integrate these techniques within the overall sensemaking enterprise.

The limitations previously imposed on the size of datasets and the kinds of data types that could be processed are rapidly disappearing. Data are no longer collected and siloed on physical storage systems, and researchers no longer need physical access to the storage medium or hardware that enables persistent connections to the siloed storage. It is not coincidental that descriptions of data access in virtual space use water metaphors to describe the experience: data streams, data flows, the fire hose of information, etc. These new ways of conceptualizing the very access to data enable previously unimaginable possibilities for new technologies to analyze, visualize, and test research hypotheses.

The social science community has yet to fully realize the analytic potential that big data may offer. Here we examine those analytic capabilities most applicable to visualizing understanding within the social context. These capabilities include analytics of social networks using big data, cross-channel analytics, emotion and sentiment detection, and agent-based modeling to advance intelligence analysis of crowd behavior.

6.1. Social Network Analysis Using Big Data

Big data describes much of the social media output and includes real-time analysis of volumes of Twitter feeds, Facebook updates and photo posts, blog posts, video feeds, and satellite streams. While the popularity of these social media sites is astonishing and continues to expand, the analytical community continues to debate the most advantageous means to collect and analyze these data. Preis, Moat, Stanley, and Bishop (2012) give an example of analyzing Web search logs using Google Trends to identify potential patterns in the data and found a unique correlation between online behavior and the economic indicators of the country in which the user resides. Their study clustered Internet searches into those including search terms of '2009' and earlier and those with '2011' and later. The research found that Internet users in wealthy countries performed far more future-oriented searches than Internet users in countries with low gross domestic product (GDP). Users in those countries searched more often on past events (Figure 15).

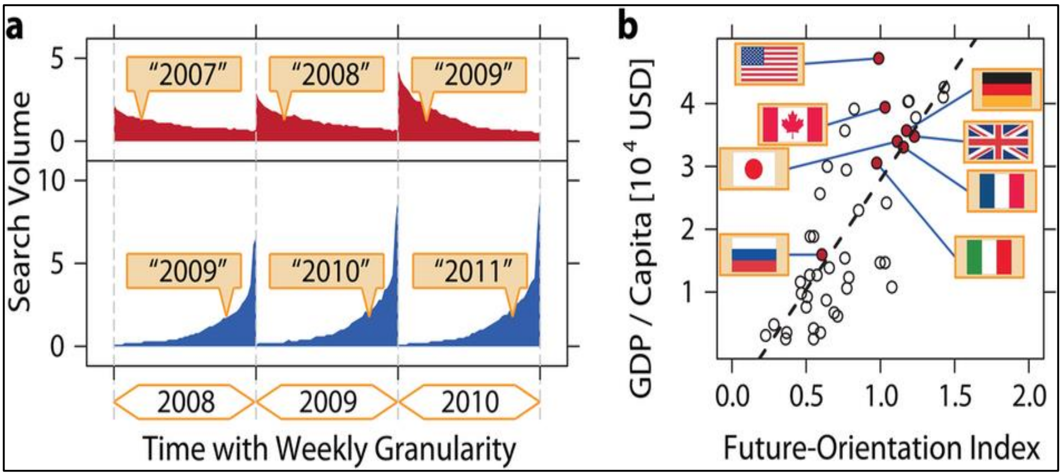

Figure 15. Internet search of the future vs. the past based on country GDP. Adapted with permission from Preis, Moat, Stanley, & Bishop (2012).

While such results can be construed as a discovered correlation, determining whether they indicate cultural trends or are merely a happenstance of the experimental design remains an ongoing issue in big data analysis. Because the data are by and large unstructured, forcing structure onto the data can mask actual relationships while simultaneously imposing artificial trends or correlations that are artifacts of the data processing routines used to filter the data.

The data used to generate Figure 15 provide a snapshot of log files for websites throughout the Internet. Analyses of these data demand that researchers cull massive data sets, extract meaningful relationships, and assess the effectiveness of those relationships. However, big data also affords researchers the possibility to further hypothesize and visualize these data to include geographic determinates of these more future-oriented countries. For example, do specific future-oriented ideas link Germany, Britain, France, and Italy while simultaneously rendering the relationships between the United States, Canada, and Japan more restricted? Is Russia a transitional country moving from a past-oriented society to one that is predominantly future-oriented—and, if so, what driving forces within this society are causing this shift of perspective? Such pattern recognition can lead to new insights into the inter-workings of these countries as part of the massive overhaul of social institutions they are currently experiencing.

6.2. Cross-Channel Analytics with Emotion Detection

Cross-channel analytics—the study of interactions across organizations or across different media channels (e.g., print, audio, websites, or mobile devices)—uses big data to track, link, and analyze social actors and their interactions. Tracking an individual's behavior across a multiplicity of communication channels is not new in social behavioral research; however, using analytics to amass volumes of varied data and process these data at the computational speeds afforded by high-end computing systems will open a new field of investigation with respect to understanding and visualizing the underlying social dynamics.

In conjunction with cross-channel analytics, researchers need new tools to exploit and better understand sentiment among social actors. Detection of an individual's emotional state (e.g., anger, confusion, happiness) through voice channels illustrates how social science researchers can use the new tools and technologies to further explore dynamic social interactions. Sentiment analysis applies equally to verbal messaging and text messaging; as these new detection technologies become available, the interrelationships among emotional connections, sentiment analysis, and social interactions will be more readily accessible.

Currently, emotion detection is a key underlying variable in training physicians to treat patients suffering from post-traumatic stress disorder (PTSD), especially patients who perceive the condition as a personal failing. The Defense Advanced Research Programs Agency (DARPA) Detection and Computational Analysis of Psychological Signals (DCAPS) project applies machine learning, NLP, and computer vision to generate training scenarios for physicians. In these scenarios, the virtual patient displays a range of facial expressions in an attempt to mask symptoms or deceive the physician regarding his or her emotional state. This simulation technology enables DCAPS to program the virtual patient to allude to signs of PTSD or display emotional clues indicative of PTSD that the physician learns to recognize during a medical evaluation.

Equally compelling is that the virtual patient can be programmed in real time using an amalgam of sensors that simultaneously perceive the physician's body language and physical signals during the simulated diagnostic session. The virtual patient can modify his or her responses based on the physician's level of ease or discomfort given the context of interactions. In this way, physicians become aware of their own influence on the diagnostic interview and how their actions may either help or hinder patients in discussing their symptoms.

6.3. Gaps in Visualization of Understanding

Social analytics of big data has tremendous potential for predictive analysis and modeling of associated trends. The patterns and connections uncovered using big data can be disseminated in near-real time to subsequent models designed to address specific behaviors or associations. For example, business intelligence tools can be integrated with data mining algorithms to foster automated discovery and generate output in formats such as near real-time simulations, increasingly complex semi- and full-immersion animations, and more granular summary tables based upon hitherto unknown associations. Filtering of Internet search terms using link analysis, for example, could reduce the nodes in a social network to those representing specific behaviors among actors with particular affiliations.

Adoption of social network analysis, however, has been hampered by the perception that the process is highly abstract and that the information collected is difficult to translate into intelligible actions. Further, the design of association algorithms and search indexing routines can lead to questionable methods that may cause researchers to draw conclusions based upon misunderstandings of the scope and accuracy of the methodology. Moreover, lack of experience with big data highlights the need for well-defined data governance at all levels of research, and for standards and best practices to guide the implementation of big data in the social sciences.

Considerable barriers still limit the uses of big data and the tools, processing modes, and modeling capabilities that big data promises. For example, the lack of sufficient analytic capabilities to mine social media for relevant patterns and correlations against background noise presents a significant hurdle to the integration of big data visualization practices. While big data opens a new field in data processing and visualization, the very tools for modeling and visualizing this output require new modes of conceptualizing behavioral modeling as a practice. Today's challenge in distinguishing the signal from the noise is only amplified when static datasets become part of a data stream.

Aside from the technical requirements of new modeling methodologies, concerns related to privacy rise to a new level with respect to big data. General users of social media may come to feel so constricted in their use of the media by extensive online profiling that they may choose to abandon the media altogether. Conversely, users who know how they are expected to behave may begin using social media to better align their online presence with expected behavior. In addition, aggregating data about individual behaviors based on an Internet search index is not the equivalent of social behavior. Researchers need to be sensitized to better appreciate the nuances of this new data environment.

Another significant factor preventing the full integration of big data in understanding and visualizing social behavior is the role that anonymization (the processing steps used to obfuscate an individual's identity during data analysis) plays in protecting individual identities. Online privacy and corporate liability in the event of a security breach or a leak of private information have received considerable attention, but the research community does not widely appreciate that while the principles of privacy are considered sacrosanct, the means for ensuring that privacy are not foolproof (Ohm, 2009). No one algorithm or method suffices to fully anonymize data. As in other areas in which a particular information item may be considered low sensitivity by itself, the information may become much more revealing when low sensitivity information is merged with other data.

7. New Visualization and Predictive Modeling

New models for scientific visualization have emerged that exploit the potentials of big data and promise to circumvent some of the previously discussed limitations of traditional data querying algorithms (Purchase, 2008). These new visualization methods must address data so massive that simply framing the problem to be solved can very well hinder pattern discovery. Data as a scientific inquiry unto itself and the visualization of data as a dynamic process are new ways of considering the role of data in knowledge discovery and acquisition.

This chapter has focused on visualizing the underlying baseline dynamics that increase understanding of social conditions and interactions. The technological breakthroughs of big data can better inform predictive models of social behaviors and provide more succinct visualization of multidimensional data outputs. Agent-based modeling offers one example of coupling the requirements of vast data processing to the visualization of dynamic interactions at multiple scales. Combining agent-based modeling with big data analytics to generate self-organizing maps can

further contribute to meeting the research goal of integrating individual behavioral dynamics into group dynamics across a specified domain, whether that movement occurs in a social network or a physical environment.

7.1. Agent-Based Modeling

Greater reliance on high-speed, parallel processing environments and vast improvements in virtual storage capabilities give big data a tremendous advantage over the traditional database approaches of pattern recognition, cluster analysis, and correlation studies. Coupling agent-based modeling with big data gives researchers a powerful set of tools to model human behavior and constrain that behavior by environmental or temporal boundaries. Agent-based modeling represents a new approach to generating data for visualization made possible by these environments. In this dynamic modeling process interactions on a microscopic scale are summed to the interactions that comprise the group dynamics. An agent-based model includes a population of individual "actors," with the number of actors conditioned by the needs of the model. Each actor is implemented as a distinct data structure with unique attributes specified by the model. Successive iterations of actions between individual actors and among groups of individuals build macroscopic regularity. While discrete collections of actors may perform in a somewhat homogeneous manner (group behavior), the actors are heterogeneous in relation to other groups and behave according to the dynamics of human error, peer pressure, and biased reasoning (Tsang, 2008).

Agent-based modeling also generates adaptive, interactive simulations of actors based on a set of conditions stipulated in the model development process. For example, the kinds of patterns extracted through agent-based modeling can condition the parameterization of the model in subsequent iterations. In this way, agent-based modeling not only allows for simulation of actors in a crowd and multiple possible configurations of interactions, but also integrates real environmental factors into the model that can constrain actors in their subsequent contacts with each other. In addition, a simulated environment created with agent-based modeling tools can incorporate physical barriers that actors must negotiate as they maneuver through the model. Finally, agent-based modeling can simulate hierarchical structure and visualize various alternative scenarios to explain the perceived group dynamics in near-real time.

7.2. Visualization Using Self-Organizing Maps

In the field of context awareness and artificial intelligence, a self-organizing map (SOM) is an artificial neural network that allows researchers to visualize multidimensional features in a reduced dimensional space to better understand the similarities between attributes (Hsu, 2006). In general, a SOM is structured as a topology of input and output nodes, also referred to as neurons (Skupin & Agarwal, 2008). The topology can be either trained with pre-defined weight vectors or untrained, with each input vector organized using a random weight distribution. After the SOM has clustered the input features to their most similar nodes, the resulting topology becomes available for further analysis and discovery.

SOMs provide a continuous field representation of multidimensional data reduced to lower dimensions as patterned topologies against which individual, *n*-dimensional features can be mapped and visualized within a low-dimensional space. For example, Skupin (2008) created a SOM

to visualize how a hypothetical researcher might discover similarities among seemingly disparate counties across the geographic space from Santa Barbara, CA, to New Orleans, LA, using only the multidimensional Census attributes of income distribution, household composition, and home ownership of each county visited. Traditional data analysis techniques would not have detected the clustered patterns of these attributes based solely upon a geographic distribution. This attribute-driven SOM allowed Skupin to infer distinct clustering of racial distribution and home ownership as well as the influences of household composition. In a second experiment described in the same paper, Skupin again used Census attribute data to derive the socioeconomic composition of New Orleans neighborhoods as traversed using personal transportation and public transportation. In this SOM, Skupin analyzed Census block data (comprising approximately 500 individuals within the metropolitan area of New Orleans) to reveal the distinct neighborhood compositions within the SOM's topology.

8. Understanding Within Visualization

Understanding cultural interactions demands a complex investigative process, regardless of how that understanding is visualized. While the technology for visualization, based upon data stores heretofore unimaginable, continues to improve our understanding of the sociocultural domain, the principles underlying such understanding preoccupy social science research. The promise that big data holds for expanding the visualization capabilities of predictive modeling is tempered by the very real necessities of understanding cultural and social differences in the present, which remains paramount to situational awareness and therefore a strategic priority. The proliferation of visualization techniques and methods means that researchers will require better training to appreciate the nuances of these tools and to constrain the data inputs in order to obtain predictive modeling capabilities vastly different from those currently available.

As more and more researchers begin to tackle the very real challenges of using vast data sets to investigate sociocultural problems, they must also address the need for a new ontological tenet of scientific investigation. In the past, datasets that were single-sourced, of known temporal duration, and collected in a consistent, documented manner held the researcher to a standard of problem statement, hypothesis formulation, hypothesis testing, acceptance, or rejection. Today's data challenge is how to rethink data processing and analysis using multi-source, real-time, multi-platform, and multi-formatted data. As we have argued in this chapter, traditional data analysis and testing of hypotheses for big data are inadequate to address the multiplicity of dimensions, sources, and input spaces from which sociocultural data are collected. Agent-based models that perform dynamic integration of micro-scaled actors within the larger, more complex and multidimensional group domain or SOMs that visualize input features against a reduced dimensionality topology offer two examples of how data scientists are beginning to reformulate visualization of sociocultural data to better understand the underlying dynamics that drive individuals within their sociocultural space.

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4 Training for sociocultural behavior understanding in operational environments[1]

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1. Sociocultural Behavior Understanding

From the intelligence analyst in the command center identifying deviations from typical patterns of life to the small unit leader on the ground negotiating with a village elder, the ability to understand sociocultural behavior is vital for achieving mission success. According to Schmorrow (2011), accurate analysis of sociocultural behavior requires a “thorough perception and comprehension, grounded in social and behavioral science, of the sociocultural features and dynamics in an operational environment” (p. 42).

A solid understanding of sociocultural behavior enables warfighters to recognize subtle details that reveal critical information about cultural and social norms when observing interactions in unfamiliar cultural settings. For example, Figure 1 shows a group of Somalis holding a meeting at the edge of their village. Though many individuals, even those unfamiliar with Somali culture, may immediately identify the leader of this meeting and his entourage (the group standing), they might well miss the more subtle cues in the picture that would allow them to gain a more in-depth understanding of the cultural environment. For example, the majority of the men not part of the leadership group are seated in the shade, while the women and children are seated in the sun. This observation provides information about the likely social structure of this society and the role that gender plays.

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Figure 1. Village Meeting in Somalia. Adapted with permission from UNAIDS.org (2013).

Context appreciation and an understanding of normal patterns within an operating environment are crucial for making sense of the ambiguous situations that warfighters frequently encounter. Such understanding, for example, enables a full motion video (FMV) analyst tasked with providing convoy overwatch to realize that a single shepherd surrounded by a flock of sixty sheep in a position that could provide overwatch of the route is probably not a cause for concern; however, three 'shepherds' with two sheep in the same position definitely is. Similarly, a member of a route clearance team that must ensure a route is free of improvised explosive devices (IEDs) needs a solid understanding of social, regional, and cultural features to identify and make sense of ambiguous cues. For example, the physical environment may dictate different IED emplacement tactics: command wire IEDs are primarily used on paved roads whereas pressure plate IEDs are used on unimproved roads. The visual indicators of these types of IEDs differ and can be very hard to detect, as they may include very common items (culverts, yellow jugs) or be inherently difficult to see (disturbed earth). Thus, route clearance personnel must have the knowledge to determine whether a yellow jug by the roadside is being used as a delivery vehicle for homemade explosives or to transport cooking oil. An accurate assessment of the cultural environment is critical to making sense of these visual cues.

Unfortunately, the early stages of recent conflicts in Afghanistan and Iraq demonstrated a clear capabilities gap: military personnel at all levels received insufficient cultural training, troops on the ground were not prepared to leverage cultural information to enable mission success, and intelligence analysts did not integrate cultural analyses into their products (Connable, 2009). As

one soldier stated, “I had perfect situational awareness [in regard to things such as the location of enemy tanks]. What I lacked was cultural awareness” (McFate, 2005, p. 43).

To address these gaps, the U.S. Department of Defense has funded government, industry, and university laboratories to develop effective technology-based training for understanding sociocultural behavior. This chapter discusses these state-of-the-art training technologies and how best to bring them into operational use. We first summarize training technologies already in existence or currently in development. Next, we discuss the gaps in existing training that these technologies can help bridge as well as the challenges associated with integrating these training technologies into the operational environment. Finally, we provide suggestions on overcoming these implementation challenges.

2. State-Of-The-Art Training Tools

Given the scope of this chapter, we do not attempt to provide an exhaustive description of every available or emerging technology that supports training in sociocultural understanding. Instead, we describe existing technologies within two categories based on their primary emphases: *interpersonal interaction* and *group- or population-level dynamics*. We briefly describe the defining characteristics of each category and provide a few instances of technological tools under development or recently developed.

2.1. Improving Interpersonal Interactions

Tools with an emphasis on interpersonal interactions use text, video, or a virtual environment to present users with a scenario involving simulated interaction with foreign nationals. Independent of the medium used, training technologies typically ask users to interpret the behavior of foreign nationals within a situation and/or to choose culturally appropriate courses of action at different points in the scenario. Often, the scenarios reinforce lessons taught during a preceding multimedia tutorial for the specific culture in which the scene takes place, and incorporate multiple-choice questions to assess the user’s knowledge (and provide feedback) during the interaction.

The armed services often implement technological tools with an emphasis on interpersonal interactions to train users to understand and interact with foreign nationals within a specific culture (e.g., Afghanistan). While they expect some skill transfer to occur across cultures, the developers tailor these tools for specific cultures in order to improve the sociocultural understanding that supports face-to-face interpersonal interaction with members of that culture. Thus, they often integrate common acceptable behaviors and cultural taboos (i.e., ‘do’s and don’ts’) of the specific culture into their lessons.

Some researchers had developed structured training materials and exercises that addressed sociocultural understanding training before the advent of sophisticated computer technologies (see Bhawuk & Brislin, 2000, for a review). While these technologies do *not* represent the state-of-the-art, they deserve special mention as the predecessors of many technologies described in this section; they also had an impact on the training techniques currently used in cultural training

schools. For example, culture assimilators (Fiedler, Mitchell, & Triandis, 1971) are self-administered, structured training programs that use scenarios to expose users to cross-cultural interactions and misunderstandings. Users answer multiple-choice questions regarding their understanding of the incident and receive tailored feedback (by being directed to different pages) regarding the appropriateness of their answer and the rationale behind it. Culture assimilators have undergone extensive evaluation (Bhawuk & Brislin, 2000) and have influenced the development of both training curricula and technological tools. Most of the more technologically sophisticated tools discussed below follow similar formats, but leverage video and virtual environments in an attempt to create higher fidelity and more engaging scenarios. They also have the potential advantage of providing detailed situational context that text-based scenarios would lack and that would have to be provided by a human instructor.

Human-Actor-Based Cultural Scenarios

These technological tools feature human actors playing the roles of U.S. military personnel and foreign nationals in a cross-cultural scenario. While they present details about the scenario in a relatively passive way (i.e., no user input), movie-quality videos facilitate ‘immersion’ in the situation and engagement during the sensemaking and decision process. Army 360 and Visual Expeditionary Skills Training (VEST) fall into this category. Because the two have similar structure and format, we only describe Army 360, which resulted from a 2008–2009 partnership between the Army and InVism, Inc. Each scenario in Army 360 is preceded by a ‘mission briefing’ — a multimedia tutorial with information relevant to the upcoming scenario, and a pre-scenario quiz to estimate the user’s baseline knowledge. Since these elements of the tool are specific to the culture of interest, these tutorials impart culture-specific knowledge. After users complete the pre-scenario quiz, Army 360 presents them with movie-quality reenactments of scenarios in the foreign cultural environment of interest. At different points during the scenario, the video presentation pauses and users are presented with multiple-choice questions regarding the behavior of foreign nationals or the course of action the user should take. Typically, users are expected to rely on information presented during the pre-scenario tutorial and to demonstrate learning when answering these questions. If a user makes an inappropriate choice (e.g., asks an Iraqi sheik to skip his prayer so that they can finish their discussion), scenarios present negative consequences associated with the action (e.g., the Iraqi sheik angrily walks out of a key leader engagement).

Today, U.S. soldiers and airmen can access Army 360 and VEST through the Army’s Training and Doctrine Command (TRADOC) Culture Center and the Air Force Culture and Language Center (AFCLC), respectively. Versions of these systems are available for a range of countries, including Iraq, Afghanistan, and Somalia. The authors are unaware of any formal evaluation conducted to assess the effectiveness of these tools to improve the sociocultural understanding of warfighters in operational settings.

Avatar-Based Cultural Scenarios

These technological tools rely on virtual environments and avatars (instead of human actors) to present cultural scenarios similar to those described above. Avatar-based cultural scenarios offer the distinct advantage of greater customizability over counterparts that use human actors, since

the reactions of the avatars can be better tailored to the user's choices and actions (Sagae, Ho, & Hobbs, 2012).

The Virtual Cultural Awareness Trainer (VCAT), developed by Alelo for Joint Knowledge Online (JKO), falls into this category. Like the tools introduced above, VCAT combines multimedia tutorials that introduce users to relevant cultural knowledge (i.e., "knowledge-oriented learning activities," Johnson, Friedland, Schrider, Valente, & Sheridan, 2011) and scenarios that require users to make decisions about the meaning of the foreign national behavior and preferred courses of action (i.e., "skill-oriented role-playing scenarios," Johnson et al., 2011). During the scenarios, the user controls the behaviors and communications of the avatar representing the U.S. warfighter. The behavior of the avatars representing foreign nationals responds to the user's choices. For example, "characters will reciprocate and become more friendly and cooperative" when users engage in appropriate behavior and build rapport with foreign nationals (Johnson, Friedland, Watson, & Surface, 2012, p. 17). VCAT also includes supplementary materials regarding language (e.g., key phrases for the region), gestures, and advice from experienced warfighters in the form of interviews.

While the authors could locate no specifics on evaluations, Johnson (2013) reports having "conducted studies to evaluate both the immediate and long-term effectiveness of VCAT training. Surveys of learners and their supervisors, conducted after the learners had deployed overseas, indicated that the training had long-term benefits" (Johnson, 2013, p. 2). VCATs for Northern Africa, the horn of Africa, South America, and Afghanistan are available through JKO; Alelo reports it is also developing VCATs for Central America, the Caribbean, China, and Southeast Asia (Alelo, 2013).

2.2. Understanding Group- or Population-Level Dynamics

The second group of technology-based tools aims at developing observation skills so that users can better understand key features of unfamiliar cultural environments. While these tools are typically implemented for specific (or sets of specific) cultures, they are designed to train culture-general skills that the user could then apply to any novel cultural environment. For example, these tools emphasize searching for patterns of behavior in the environment so that users can better understand what is normal in that setting (i.e., 'baseline' or identify 'patterns of life'), and consequently develop the ability to identify deviations from the baseline. As illustrated in the subcategories below, tools within this category vary in their technological sophistication and degree of interactivity.

Again, structured training exercises that predated the development of more sophisticated technological tools deserve some mention here. In particular, simulation games, such as BaFa BaFa (Shirts, 2013), have certain commonalities with technological tools under this category. While BaFa BaFa has had greater influence on training schools than on the state-of-the-art technological tools presented below, this structured exercise constitutes an example of an early attempt to systematically train culture-general observation and sensemaking skills. BaFa BaFa consists of a 1.5-hour group exercise in which two subgroups are assigned to two fictitious cultures and asked to behave according to a set of cultural rules. One member of each subgroup is tasked to observe the

behavior of the other subgroup and learn as much as possible without asking questions. The observer then brings this information to his or her subgroup, the subgroup members then collaboratively attempt to make sense of the other subgroup's culture and formulate hypotheses about the most effective way to interact with the members of that culture.

Multimedia Tutorials

Multimedia tools typically include an instructor-guided lecture, as well as audiovisual demonstrations of the concepts being explained.[2] The video medium facilitates independent, on-demand learning, as well as the use of realistic examples. In all of the instances we found, these tutorials were used to complement other training methods (e.g., interaction-oriented technologies, human-administered training).

As an example, the Marine Corps Warfighting Laboratory developed Combat Hunter Computer-Based Trainer (CBT) to support human-administered training that facilitates a more proactive mindset in operational settings. Specifically, the tool aids in training Marines to look for patterns of life so that they can more effectively identify "what is here that should not be here; and what should be here that is not" (Hilburn, 2007, p. 60). Drawing lessons from rural hunters, individuals from inner-city backgrounds, law enforcement officers, and experienced warfighters, the Combat Hunter CBT includes a series of tasks and exercises aimed at developing users' observation, profiling, and tracking skills in operational settings. A series of instructor-guided tutorials targets the skills (e.g., observation, profiling) to be learned, as well as the use of tools (e.g., binoculars) to enhance performance. The CBT prepares participants for the Combat Hunter training by providing some of the declarative knowledge beforehand and enabling human trainers to spend more time interacting directly with users to train them in the desired skills (Schatz & Nicholson, 2012).

The Combat Hunter Fact Sheet (Office of Naval Research, 2013, p. 2) reports that "empirical outcome testing" conducted "with control and experimental groups of Marines at the School of Infantry East in September and October 2010 … validated the utility, engagement, and instructional efficacy of the software." The Marine Corps currently uses the Combat Hunter CBT in its training program.

Interactive Data Visualization

Accessing relevant and reliable sociocultural information about countries of interest and directly comparing these countries along key dimensions often presents a challenge. Interactive data visualization offers a centralized medium for obtaining comparable data on key dimensions across countries. Moving away from an exclusively text-based medium can assist users to better explore trends within a country, compare high-level cultural variables to U.S. norms, and generate expectations for upcoming deployments.

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[2] The pre-interaction tutorial used in conjunction with the interaction-oriented technologies described in the previous section would also fall under this multimedia-tutorial category. However, those technologies emphasize culture-*specific* practices and knowledge rather than culture-general skills.

The visualization tool in the Preparation Module of CultureGear falls into this category. 361 Interactive, LLC, is developing CultureGear under the sponsorship of the Office of Naval Research (ONR). The visualization component aids users in directly comparing critical cultural dimensions across multiple countries and/or within a single country across time (McCloskey, Behymer, & Mateo, 2012). For example, Figure 2 shows that the user has selected ‘population growth rate’ from the Social Factors tab of the menu. The population growth rate for each country is represented graphically on the world map via color coding, with warm colors (red, orange, yellow) representing positive growth rates and cool colors (blue, green) representing negative growth rates. A quick glance can show the user that the population of Europe is declining while the population of Africa is on the rise. A comparison analysis tool enables the user to gain more information about a particular country’s population growth rate over the past few years and to view trends of multiple countries side by side. The information currently used in CultureGear’s Preparation Module is imported from the online Central Intelligence Agency (CIA) Factbook. While reception by military cultural trainers and leadership has been positive, the Preparation Module has not yet been formally evaluated or integrated into Armed Forces programs.

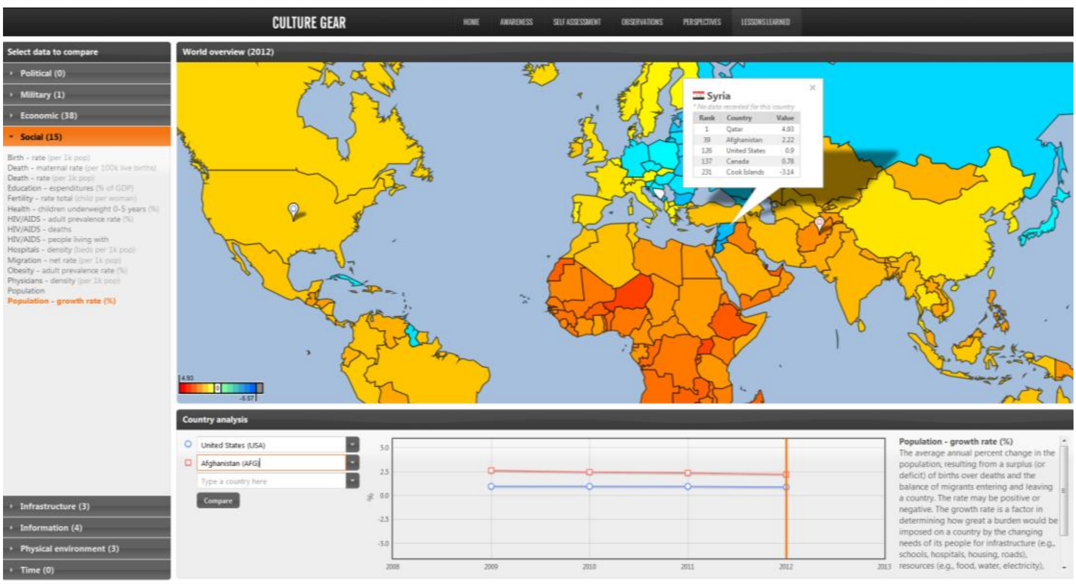

Figure 2. Screenshot of CultureGear’s interactive visualization tool.

Interactive Tools Using Real-World Imagery

Interactive tools utilizing real-world images to train the perceptual/observational skills of warfighters typically ask participants to identify and explain aspects of a scene that are relevant for sociocultural understanding. Both the Observations Module of CultureGear and the Difference-Spotting Exercise of Combat Hunter fall under this category. The Observations Module of CultureGear consists of a collection of geo-tagged images depicting scenes from actual U.S. Army deployments (many images include both U.S. forces and foreign nationals). Users are asked to tag

the critical elements or aspects within each scene that are relevant for sociocultural understanding and to explain the sociocultural relevance of those elements or aspects. After submitting their responses, users compare their selections and rationales with those of a consensus of culturally experienced warfighters and cultural experts (see Figure 3). Users also complete a quiz about their understanding of the scene. Again, they can check whether their answer to each question matches the experienced warfighters' responses and the aspects of the scene that experts used to make their assessments.

Researchers recently assessed the effectiveness of CultureGear in improving observation performance among junior warfighters (Mateo, Behymer, & McCloskey, 2013). Users who received CultureGear training showed faster and more accurate performance than control participants during observation tasks. No operational forces currently use CultureGear, but 361 Interactive has a teaming agreement in place with the John F. Kennedy Special Warfare Center and School (JFKSWCS) to support its integration into their operational training curricula over the next three years.

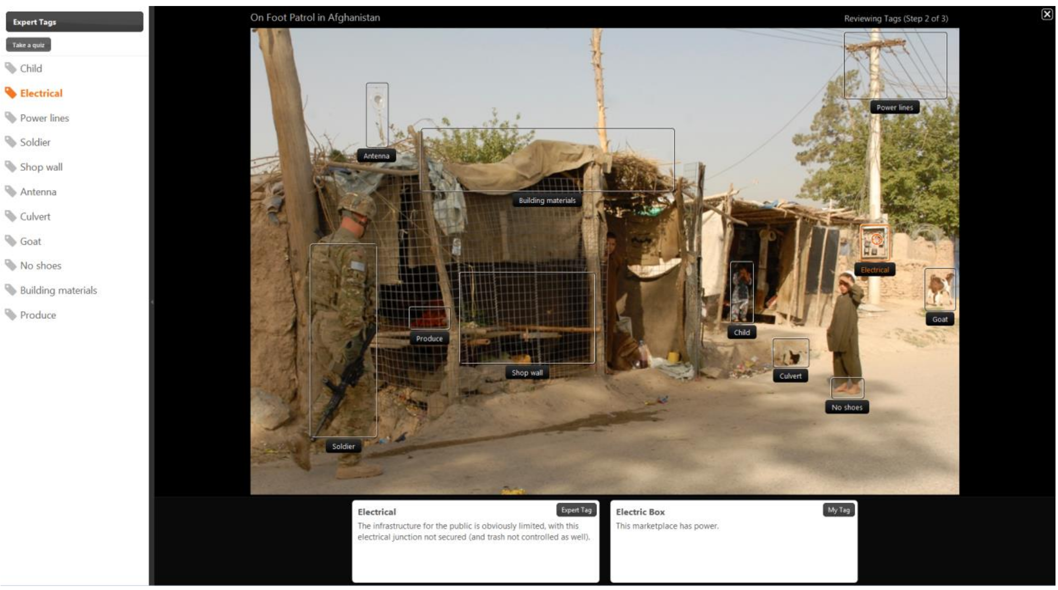

Figure 3. Screenshot from CultureGear's Observations Module.

The Difference-Spotting Exercise of Combat Hunter involves the presentation of two seemingly identical scenes and asks users to identify the differences between them. According to Hilburn (2007), Marines can access these exercises while deployed to practice their observation skills.

Developers are also building interactive tools using real-world imagery to assist intelligence, surveillance, and reconnaissance (ISR) analysts in understanding unfamiliar cultural environments. The type of imagery used for the ISR domain is more typically a bird's eye view of the scene than a

ground-level perspective. However, tools such as the Cognitive Desktop Analysis Trainer (C-DAT) use a procedure similar to those used in the Observations Module of Culture Gear and the Imagery Exercise of Combat Hunter. C-DAT shows FMV analysts both simulated and real-world FMV and asks them to identify patterns of life and recognize deviations from normal activities (e.g., unexpected individual behaviors) in real time. Users also answer questions that probe their sociocultural understanding of the cultural scene. For example, in Figure 4 the trainee has correctly identified a construction crew working on a mosque as an item of interest and now must select why this event is significant from the list on the right. If the trainee gives an incorrect answer, the tool highlights the correct answer and explains the rationale behind that choice. C-DAT also has a game-like scoring system to increase engagement and competitiveness among trainees. As C-DAT is an experimental tool currently under development, its effectiveness has not been formally evaluated, nor has it been employed in operational settings.

Figure 4. Screenshot of C-DAT Training System.

Interactive Tools Using Virtual Environments

Like interaction-oriented technological tools, interactive tools with an emphasis on understanding group- or population-level dynamics could leverage virtual-environment technologies. To our knowledge, no current technological tools use virtual environments and avatar-based scenes to improve the perceptual/observational skills of users beyond interpersonal interactions. However, ONR has funded the PercepTS project to create such a tool. Following the Combat Hunter philosophy, this project aims at developing a virtual training environment ("Virtual Ville") in which participants can complete Combat-Hunter-like training (Schatz & Nicholson, 2012). This project is expected to be completed in the 2015–2016 timeframe.

3. Science And Technology Gaps

3.1. Lack of Training Tools for Intelligence Analysts

"Although the Intelligence Community is full of world-class expertise on foreign peoples, places, and organizations, this industry rarely isolates and illustrates culture as a factor deserving its own sophisticated and thorough treatment." (Johnson & Berrett, 2011, p. 2)

Current training efforts and those in development seem to focus primarily on small unit leaders interacting with foreign nationals on the ground. Many existing and emerging tools are designed to improve understanding in the context of one-on-one interactions as opposed to understanding group or population-level dynamics. By contrast, almost no training tools exist for the intelligence analysis and strategic planning levels, even though dramatic changes in sensor technologies and the nature of warfare over the past several decades have made it increasingly important for ISR analysts to have sociocultural understanding to successfully detect and interpret critical events.

During the Cold War era, ISR analyst tasking was relatively simple, perhaps involving monitoring of an adversary's physical assets, including tanks, missiles, and planes (Bryant, Johnson, Kent, Nowak, & Rogers, 2008). Today's ISR analyst, however, may be tasked to detect, observe, interpret, and predict patterns of life activities—for example, to identify networks associated with terrorist cells—while simultaneously assessing the cultural and contextual aspects of the surrounding regions. The same visual stimulus—a man digging near a road—might represent a critical event that the analyst must not only detect but also understand within its context: Is that individual a farmer digging a trough for water or an insurgent emplacing an IED?

Despite the challenges facing intelligence analysts and the limitations of existing training, little research has focused on designing effective training to develop analytic skills. Existing pre-mission training often focuses on basic intelligence principles and analysts only gain an understanding of sociocultural behavior through on-the-job training. This often places analysts in difficult situations. Rather than beginning their training with a relatively simple task (e.g., calling out vehicular traffic in a rural setting), many analysts must learn by confronting a very complex real-world mission scenario that involves monitoring multiple named areas of interest while trying to fulfill multiple customer intelligence requests.

3.2. Valid Content Often Missing

Tool designers often place too much focus on developing the training technology as opposed to developing the content to populate it. To be useful, training in sociocultural understanding must rest on a solid understanding of real-world constraints. One useful method for developing training content is the decision requirements table (DRT), a technique developed by Klein Associates, Inc., which captures the critical cues that experienced analysts use when making a cognitively demanding decision (Phillips, McDermott, Thordsen, McCloskey, & Klein, 1998). The DRT can also capture why a decision is difficult, the information sources that experienced analysts consult to inform their decision, the common errors novices make when reaching a decision, the strategies used by experienced analysts, and the sources of uncertainty.

Table 1. *Sample, partial DRT*

Challenging Decision	Why Difficult?	Cues	Factors/ Info Sources	Common Errors	Strategies	Uncertainty
Evaluate the economy in the AO	Unregulated activities are untaxed and therefore, difficult to account for (little written information or standard policies followed) Civilians are often afraid to discuss black market activities with US forces It may be difficult to determine who participates in informal activities Informal activities may be conducted from a home or in hard-to-find locations May not be clear how the formal economy relies on the informal economy	Flow of goods Prices of necessities such as gas/benzene/ foodstuffs Overt presence of black market Observed levels of business at both proper and informal marketplaces Types of currency that are predominant Reactions of civilian populace when questioned regarding black markets Perceived individuals who seem to control the distribution of goods	Regional differences in what is legal and acceptable Local laws and customs Prior activities Intel from informants Presence of barter systems/symbolic exchange systems Legal currency Local perception of equity of distribution of goods and services Economic rhythms of a community (migration, planting, harvesting, market day, work hours) Distribution of wealth	Assume that only formal and legal activities account for the economy Attempt to break down the informal economy w/ no understanding of effects Fail to consider long-term effects of actions. Implement an operational plan that blocks access to critical goods and services. Force same price structure on both formal and informal economies Fail to "dig deeper" into underlying issues when questioning local populaces Force or assume own value system on local economy	Address inequities Monitor illegal activities Recognize the role of women and children in the informal economy Recognize social customs and norms in regards to place of work (women may need/want to work in the home rather than a factory) Mentally simulate effects of actions on longer-term economic health and stability of AO. Use force to impose Western values on system	Who is bribing and blackmailing whom What civilians are really thinking versus saying How will Marine operations impact the informal economy On what commodities and services does the informal economy really focus What is the true price of imposing immediate stability (3rd order effects) Who is truly controlling the informal economy

Table 1 shows a sample partial DRT based on a small set of cognitive task analysis (CTA) interviews conducted with the leaders of small Marine Corps units. The decision requirement is identified at the top of the table and the first column describes some specific reasons that can make this decision particularly challenging. In this case, the reasons why interviewees found economic analysis challenging in the context of specific situations included that informal economic activities are hard to recognize and are unregulated, and that individuals are often reluctant to discuss them. The second column describes the cues that can help analysts evaluate the economy, such as overt signs of black market activity. The third column describes information sources that individuals may consult when making the decision or knowledge they need to have (e.g., rules and laws regarding what activities are legal in a region). The fourth column identifies common errors that novices might make (e.g., assuming that only formal, regulated, and legal activities are part of the economy). The fifth column lists strategies that experts may use to support their decision making, such as active monitoring for illegal/unregulated activities. The final column identifies common sources of uncertainty that may increase the difficulty of making an assessment or decision.

DRTs can be used in several ways to direct scenario development. They serve as sources of information about how to make a scenario more or less challenging. They also indicate means for evaluating the trainees' decisions during a scenario by outlining common errors and successful

strategies and by denoting the knowledge that should be presented or available to trainees within or before the scenario as well as the resources trainees should be able to access. They also contain the critical perceptual cues that should be represented within cognitively authentic scenarios.

3.3. Limitations of Frameworks as a Tool for Understanding

While frameworks are typically seen as useful tools to aid understanding of new environments, they may lead to oversimplification of sociocultural complexity. Additionally, training tools based on these frameworks often assume that warfighters can ascertain ground truth. For example, one of the tools we examined presents trainees with the following information: “In Iraq, Shia Muslims typically wear black-and-white headdresses while Sunni Muslims wear red-and-white headdresses.” Trainees are then shown a video of an Iraqi wearing a black-and-white headdress and asked to identify whether he is a Shia Muslim or a Sunni Muslim. Compare this situation to the following training scenario, derived from a real-world incident described to us during a CTA interview:

> It is now the third month of your mission and you have established a friendly, yet fragile, relationship with a local village elder. One day during a standard patrol of the village, your interpreter begins a conversation with a trusted “source” on the street. The source tells your interpreter that one of the top insurgents in the country is holing up in a house on the far side of the village. To capture this insurgent would put a major dent in the insurgents’ networks. You head toward the house and on the way you come across the village elder. You inform him of this intelligence and he immediately gets visibly upset. In that house, he tells you, is one of the most respected families in the village, and they are close personal friends of the elder. He assures you that your intelligence is wrong and that there is no way they could be holding this insurgent. If you raid the house, he says, the entire village will be very angry, including himself and his councilmen, who have just arrived and who seem as irritated as he is.

In this far more complex situation the warfighter cannot establish ground truth before taking action. If the warfighter opts to raid the house and the insurgent is not there it could have tragic consequences for U.S. forces’ relationship with the village elder and the village. If the warfighter decides to trust the elder and it turns out that the insurgent is in the house, not capturing him may have tragic consequences for U.S. forces.

To prepare warfighters for this type of ambiguous situation, cultural training must teach trainees “how to think” rather than “what to think.” Training limited to “this category of people wear this kind of clothing” offers little help for understanding sociocultural behavior; instead, training should focus on developing the skills necessary to make informed decisions in complex cross-cultural situations (Salmoni & Holmes-Eber, 2008).

3.4. Lack of Easily Updatable Training Tools

During the past ten years many developers of cultural training tools, whether cultural-general, region-specific, or language tools, had a specific goal: supporting warfighters deployed to Afghanistan and Iraq. To this end, the majority of training tools we have reviewed use training scenarios set in one of these two countries. However, the U.S. military has already withdrawn from

Iraq and is planning to withdraw from Afghanistan. Thus, end users may not have a positive view of training whose content focuses solely on these countries. As one trainer told us, "We're out of Iraq, I don't care about Iraq."

As the military cannot predict future deployment locations with complete accuracy, warfighters must be prepared to understand sociocultural behavior whether they will assist in disaster relief efforts in Haiti, provide intelligence to North Atlantic Treaty Organization (NATO) forces operating in Libya, or intervene in failed nation-states such as Somalia. Effective training tools should include scenarios in multiple cultural environments with the goal of imparting skills that can be effective in any cultural environment. Even region-specific training tools should include mechanisms that allow the trainers who use them to easily update existing content or generate new content appropriate to the next conflict. Both cultural trainers and trainees may soon view a training tool that cannot be easily updated as obsolete.

3.5. Lack of Empirical Validation

Few of the technological tools developed to improve warfighters' sociocultural understanding in operational settings have undergone significant empirical validation. This gap applies to both didactic methodology and content.

Didactic Methodology

The tools described in the previous section use various means to promote trainee learning. For example, Combat Hunter CBT, Army 360, and VCAT include a tutorial as part of their didactic methodology, whereas CultureGear does not. Most (e.g., Army 360, VEST, CultureGear's Observations Module) include quizzes as part of their testing/feedback mechanism, but others do not (e.g., Combat Hunter CBT, CultureGear's Preparation Module).

Tools provide performance feedback along a continuum from direct/explicit to indirect/implicit. For instance, some of the tools with quizzes (e.g., CultureGear's Observations Module, C-DAT) give explicit 'right/wrong' feedback to trainees and explain the rationale; other tools (e.g., Army 360, VEST) provide 'right/wrong' feedback by allowing learners to experience the consequences of their choice; and avatar-based tools include more implicit feedback (e.g., increasingly subtle changes in avatar behavior when the user engages in appropriate behaviors). For the most part, these tools do not incorporate any explicit mechanism to encourage practice of appropriate behavior among trainees. However, game-based tools such as C-DAT do convert performance into a score that trainees attempt to maximize, thus encouraging trainees to supply appropriate responses and compete successfully with peers.

Independent of the content taught, a tool must demonstrate its ability to effect change in the trainee. Quantitative evaluations of didactic methodologies used in tools to enhance sociocultural understanding are rare (see Mateo et al., 2013, for one exception). Even rarer are comparisons across different didactic methodologies to determine the most effective feedback mechanisms and guide the development of future tools to enhance sociocultural understanding.

Content

While ensuring that a tool can improve trainee knowledge is an important first step, military organizations must also know that the resulting change will ultimately have a positive impact on sociocultural understanding and performance in operational settings. Imagine for a moment that you have two weeks to provide cultural training to a class of 20 warfighters. Researchers from a government, industry, or academic laboratory present you with a cultural training tool that, on the surface, appears to fit well with your training curricula. Before you decide to spend your limited amount of time and departmental resources on incorporating this tool into your curricula you want some assurance. How can you know that this tool will actually improve trainee performance? In other words, how valid is the content of the training tool?

Accurate measurement of mission effectiveness, especially as it relates to the role played by sociocultural understanding, is critical to validate training technologies. Existing training rarely has good assessment techniques to evaluate the usefulness of the content as it relates to performance in operational settings (mission effectiveness). Unfortunately, little empirical evidence exists to demonstrate that cultural training improves the mission effectiveness of warfighters (DeCamp et al., 2012). A key reason for this lack of empirical content validation lies in the lack of adequate methods for measuring mission effectiveness (DeCamp, Meadows, Costa, Williams, Bornmann, & Overton, 2012). The Department of Defense would benefit from methods that can measure and assess individuals' understanding of sociocultural behavior in an operational environment.

4. Barriers To Adoption

In the authors' experience, several barriers currently inhibit the adoption of technologies to support cultural training. All these challenges may have a common feature: the inherent complexity and uncertainty of the underlying constructs that such training addresses. Typical training efforts have clear and certain objectives: they train warfighters to be better marksmen, more knowledgeable tacticians, or clearer communicators. But the competencies that underlie the inherently complex construct referred to as sociocultural understanding are still under debate within the research and operational communities. Should training focus on affective attributes (e.g., changing perceptions, biases, and attitudes), behavioral skills (e.g., developing better persuasive techniques), or cognitive skills (e.g., observing and interpreting intercultural dynamics in complex environments)? The answer seems to be a combination of all three, and likely depends upon the mission sets of the specific recipient group.

Cross-cultural skills remain a nascent concept within the military training and research communities, and are associated with a wide range of theoretical models and guiding frameworks. Each military branch (and within-branch training group) must choose the most appropriate foundations for its purposes. As a result, discord abounds over the identification of the "one best" cultural competence model to promote, or the single set of baseline skills to train.

4.1. Training Differences among Military Branches

"The cultural awareness training landscape is diverse, with an array of textures, colors, and hues. Proverbially speaking, what is missing from the picture is the frame" (Alrich, 2008, p. 2).

In a study that sought to describe cultural training programs within the U.S. military, Alrich (2008) discovered a diverse and varied cultural training landscape that contained a large number of programs with differing theoretical foundations, user populations, and missions. Each training center has its own preferred theoretical frameworks and training objectives for sociocultural understanding.

For example, the U.S. Army's JFKSWCS, which provides training for Army Civil Affairs, Psychological Operations, and Special Forces soldiers, uses the PMESII-PT (Political, Military, Economic, Social, Infrastructure, Information, Physical Environment, and Time) model to train soldiers in understanding sociocultural behavior in operational environments. JFKSWCS offers two courses that focus on sociocultural understanding: *Foundations of Cross-cultural Competence (FC3)* and *Regional Analysis.* In the FC3 course, students gain understanding about the components of culture by examining their own cultures, learning how to manage their perceptions about other cultures, and investigating how other cultures view U.S. culture. Specific learning objectives (McCloskey, Behymer, Papautsky, Ross, & Abbe, 2010) include: identify the components of cross-cultural competence that promote the development of cross-cultural competence and facilitate mission success; demonstrate an openness to alternative explanations and ideas; recognize that cultures differ in significant and meaningful ways and that these differences influence behavior; formulate accurate cross-cultural understandings and assessment of situational dynamics, the perspectives of others, and the impact of cultural actions on the broader mission as well as secondary and tertiary effects; and demonstrate the ability to consistently present oneself in a manner that promotes positive short-term and long-term relationships. The Regional Analysis course teaches students a systems approach, with the desired outcome being an increase in their cultural competencies and an understanding of countries or regions based on the application of the PMESII-PT operational variables.

By contrast, the U.S. Marine Corps Center for Advanced Operational Culture Learning (CAOCL)—the central Marine Corps agency for operational culture and language familiarization—prefers to use the Five Dimensions of Operational Culture model (Salmoni and Holmes-Eber, 2008), which states that physical environment, economy, social structure, political structure, and belief systems are especially critical to understanding sociocultural behavior. CAOCL's principal educational activity consists of managing the Regional, Culture, and Language Familiarization (RCLF) Program: a career-length program designed to instill, develop, and sustain basic language, region, and culture capabilities in career Marines. The RCLF Program uses the five dimensions of culture to provide a cross-cultural competence foundation through culture-general training (helping Marines determine what they need to know and how they can build that knowledge), culture-specific training (showing the unique characteristics of the operating area organized according to the five dimensions of culture), and language familiarization (memorizing key phrases that enable mission accomplishment).

These differences are not only found *between* Military Services: training centers within the same Service often have different training theoretical foundations and training objectives as well. For example, in contrast to the approach used at JFKSWCS, the Reserve Officers' Training Corps (ROTC)

Cultural Understanding and Language Proficiency (CULP) focuses on preparing participants in the ROTC Culture and Language Immersion Internship Program. During that three-week program the cadets interact with the local populace (in countries such as China, Egypt, Ghana, Mongolia, Morocco, Russia, Senegal, Taiwan, and Tanzania) to perform a variety of humanitarian missions. The cadets strive to achieve cultural competencies based on the Army Culture and Foreign Language Strategy Objectives (2009). A sample objective is:

> Demonstrates an awareness of own cultural assumptions, values, and biases and understands how the U.S. is viewed by members of other cultures; applies perspective taking skills to detect, analyze, and consider the point of view of others and recognizes how own actions may be interpreted.

These differences in training methods and objectives create several challenges for developers of training technologies who hope to create tools that are easily generalizable across branches of the Armed Services. Despite the similarities between the PMESII-PT model and the Salmoni & Holmes-Eber model, differences in terminology can alienate both trainers and trainees. Even simple visual differences can displease potential end users. For example, during a presentation of an early version of the CultureGear tool at a cultural training center, a trainer expressed irritation that a camouflage pattern on the main screen came from a different branch of the military. While technology developers may have little difficulty adapting a camouflage pattern for each service, trying to incorporate a framework with different terminology throughout an entire training tool (e.g., replacing PMESII-PT with the Five Dimensions of Operational Culture) presents significant difficulty. Developers hoping to transition their state-of-the-art training tools into operational use must successfully navigate this complex cultural training landscape.

4.2. Lack of Communication Between Trainers and Technology Developers

When the need for cross-cultural competence training became clear, the U.S. Armed Forces created training centers and tasked them with incorporating culture within their existing curricula or developing techniques to train cross-cultural warfighters (Alrich, 2008). At the same time, the services directed researchers and technologists from government, industry, and university laboratories to develop technological solutions to support training in cross-cultural competence. Although these two lines of research and development have evolved in parallel over the past ten years, they have not communicated effectively. Technology developers have often focused their time and energy on technological advances (such as increasing the physical fidelity of virtual worlds) as opposed to determining how the end product could best support the most likely end users: trainers and trainees within military cultural training programs.

If technological tools are to be systematically integrated and utilized into military training centers, these technologies must rest on a solid understanding of the training truly needed, the training provided in these centers, and the standards and regulations that the training must meet, and must complement and enhance this training. Only then will the resulting training programs synergistically leverage the strengths of training and technological approaches to support the development of culturally competent, cognitively ready U.S. military personnel.

Additionally, it is often difficult (if not impossible) for training developers to identify individuals within existing training centers who will remain in position long enough to champion a new training tool throughout its developmental cycle. In many cases the key leader with whom technology developers partnered to ensure successful integration is reassigned to a different position before the tool can be deployed. In these cases, training developers must start from scratch with the newly appointed leader, who may have substantially different training goals and priorities from his or her predecessor.

4.3. Time Limitations

Time presents one of the biggest barriers to implementing new training technologies. Warfighter training schedules are already very full (Abbe & Bortnick, 2010), and existing cultural training programs must essentially compete with other training programs that warfighters must complete (Alrich, 2008). While each branch of the military has implemented a strategy for incorporating cultural training into its training curricula (Abbe & Gouge, 2012), the cultural trainers we have interviewed still struggle to fit the material they consider essential into the limited amount of time they have to teach it. Often, the training schedule simply does not leave enough time for cultural trainers to incorporate new technologies into their lesson plans if these technologies do not fit seamlessly into the trainer's existing curricula. If a new training technology requires an additional time commitment from the warfighter, or would take valuable time from the already limited number of training hours cultural trainers have with students, the operational community will not accept it.

Furthermore, cultural trainers often have only limited time available to work with technology developers. They may therefore hesitate to volunteer their time unless they both see the value of the technology and can demonstrate the value of that technology to their leadership.

4.4. Severely Limited Training Budgets

In addition to restrictions on available time for the insertion of new training technologies, the military faces increasing limits on the monetary resources available for training. While most organizations apparently consider a minimum of cultural training to be critical, that minimum typically focuses on basic knowledge of language and customs, with skills in critical assessment, awareness, and interaction viewed as nonessential. Warfighters must know to apply tactics, function as part of a cohesive team, and be masters of their weapons before the services can implement other training initiatives. Discretionary training that involves advanced technologies often comes with a hefty price tag that can be inherently inhibiting in military settings where decision makers are already struggling with continually shrinking training budgets. To achieve acceptance within military training communities, developed technologies must demonstrate that they meet a recognized critical need, can contribute to reducing overall training cost, and can accommodate training time restraints.

4.5. Inconsistent Leadership Recognition of Mission Relevance

Across the Services and levels of command, some individuals still either refuse, or are unable, to recognize the importance of cross-cultural competence for warfighters. A traditional mentality of

"we are trained to fight, not to befriend" is so ingrained in some individuals that they see cultural abilities as a weakness and a focus on cultural awareness as a way to undermine the military. This mindset has become less prevalent as military personnel continue to gain appreciation of the link between cultural competence in the operational environment and mission success, but it still lingers. Until all service members recognize the importance of cultural skills to achieving mission success, resistance to training technologies that claim to promote it will remain.

4.6. Communication Within and Among Funding Agencies and Military Branches

Currently, communication among the different military branches with regard to training in sociocultural understanding can best be described as ineffective. Alrich (2008, p. 2) states that communication between different training programs, both between and within branches, is limited by "parochialism and defensiveness" as each training program has different priorities, objectives, and terminology. This lack of communication may lead to duplication of effort, and may also inhibit the cross-fertilization of state-of-the-art training methodologies across the Services.

4.7. Failing to Learn from Previous Experiences

> We did not understand what was going on in ... We were in a foreign land among people of a different culture and mind-set. It was not possible to translate our objectives and strategies into actions taken by [them] … The information sent across the cultural divide was not the information received. There was a disconnect. One thing was said and another thing was heard. The truth is, no one knew the truth. Meaning, intent, and truth were lost in translation (Dockery, 2003, p. 93).

The above quotation could very well have described warfighters' experiences in Iraq and Afghanistan, but it actually came from a soldier assigned to an Army of the Republic of Vietnam combat unit during the Vietnam War. This illustrates that the lack of adequate cross-cultural training for warfighters long antedates operations in Iraq and Afghanistan. In fact, during the Vietnam War the U.S. Army discovered that its soldiers lacked the fundamental cross-cultural skills necessary to interact successfully with locals. As a result, the Army initiated many training programs to address this capabilities gap (Laughrey, 2008). Unfortunately, when the conflict ended the Army returned to a focus on training in conventional warfare (in response to possible moves by the Soviet Union) rather than continuing to focus on skills (such as sociocultural understanding) essential for counter-insurgency and nation-building (Laughrey, 2008). With this change in focus, the lessons learned in Vietnam were lost.

Recently adopted policies that incorporate culture into doctrine provide hope that the military will not forget the lessons relearned in Iraq and Afghanistan (Abbe & Gouge, 2012). However, the military cannot rely solely on these doctrinal changes. Training must capture the subject matter expertise obtained by soldiers who have returned from deployments in Iraq and Afghanistan so that future trainees can learn from their experiences.

5. Looking Forward: Getting Technological Tools Into Operational Use

"... effective sociocultural education requires a significant investment in resources and there is no 'quick fix' or 'shake and bake' solution" (Laughrey, 2008, p. 16).

As the previous section indicates, many potential obstacles prevent the Armed Services from implementing state-of-the-art training technologies within the operational community. The military has a myriad of cultural training centers, each with its own mission sets, priorities, and terminology. Trainers within these centers often hesitate to adopt training tools that might cut into the limited time and resources they have for training (and that may not actually improve trainee performance). Developers of training technology, on the other hand, often spend too much time concentrating on the technology itself rather than on determining how their tools can best assist cultural trainers and their trainees. All too often this results in tools that represent the state of the art in technology but do not meet the needs of the warfighter.

To overcome these obstacles, developers of training technology need to adopt a comprehensive, user-centered approach to training in sociocultural understanding. Practitioners (cultural trainers) and technologists (researchers and engineers) must work together to achieve a common goal, rather than to advance their preferred approaches to addressing the problem. This often requires a third party "translator" who can not only understand and elicit end user requirements and preferences, but also translate these into usable guidance for the developers of the technology. This 'training + technology' marriage will both improve the quality of the training program and promote the acceptance and use of technological tools in training centers—especially those that participated in and shaped the design and development of the technological solutions. For example, 361 Interactive's work with the JFKSWCS leadership and trainers to tailor CultureGear and integrate it into their training curriculum places the end users at the forefront of the development process, validating their critical importance, and ensuring that their needs will be addressed upfront. Ultimately, only a deep and thorough understanding of the needs, desires, and challenges of the operational community can ensure that the military will accept, and indeed embrace, training technologies.

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Section Two: Detecting

Sensing sociocultural factors and elements in an environment

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Capability Area 2: Detecting

"Capabilities to discover, distinguish, and locate operationally relevant sociocultural signatures through the collection, processing, and analysis of sociocultural behavior data" (Schmorrow, 2011, p. 42).

Sociocultural signatures that potentially have operational relevance cover a vast domain, encompassing the perceptions, sentiments, attitudes, and behaviors of various populations of interest. Challenges in developing a robust capability to detect these signatures are equally daunting. Such a capability depends on processing and then analyzing voluminous collections of relevant data sources, with data types ranging from raw sensor measurements to text, image, and audio data, to qualitative assessments about attitudes. The data cover varying time spans, and describe phenomena at a variety of scales and levels of detail. Further, detection requires analysts to resolve many technical issues, including the need to isolate meaningful signals in a deluge of noise, manage both structured and unstructured data, process data streams in real time, and identify rare events. The chapters in this section describe state-of-the-art capabilities available to meet some of these challenges, as well as emerging capabilities that are likely to become useful in the near future.

Data Processing

Irvine's chapter, "Transforming data into information: enabling detection and discovery for sociocultural analysis," reviews the issues involved in transforming raw data into the information that researchers need to detect interesting sociocultural patterns. The discussion focuses primarily on four types of data sources: surveys, social media, imagery, and video. Surveys provide controlled methods for collecting data about individuals and societies. Social media supply direct and timely data about the opinions of individuals, as well as the unfolding of events. Imagery is becoming an increasingly valuable source of data about societies in general as well as local attitudes and behaviors. Video contains data that can be used to analyze temporal events and detect both simple activities and complex behaviors.

Each type of data presents its own set of challenges, and the data processing methods available to address those challenges have varying levels of maturity. Numerous methods are available for analyzing the data and drawing inferences from the results. This chapter pays special attention to

two somewhat recent paradigms for conducting analysis: social network analysis, which represents the relationships among individuals and groups and facilitates analysis of the interactions among sociocultural actors; and change detection methods that can identify significant shifts in a pattern of activity or behavior.

Computational Modeling

In “Current trends in the detection of sociocultural signatures: data-driven models,” Sanfilippo, Bell, and Corley address detection of sociocultural activities and events from a modeling perspective. The prominent theme here is that analysts must “harvest” data in forms that enable them to build, calibrate, and run computational models of sociocultural phenomena. This means that parameters of data records relevant to the content categories of interest must first be extracted and measured to produce sociocultural data signatures. Many techniques are available to assist in this process. Computational models then use the data signatures to characterize the behavioral patterns of interest in the underlying data. While there are many different kinds of computational models, all can be viewed in terms of sociocultural model signatures that specify how to detect and assess sociocultural patterns.

Social media content provides some unique challenges and opportunities for computational modeling. The authors review new data harvesting methods specifically designed to address those challenges, along with examples of the kinds of models that can use social media data to detect sociocultural patterns. They also provide a brief discussion about how detection models can be used as a starting point to help make predictions.

Visualization

Even after the relevant sociocultural data have been processed, and analysts have drawn inferences with the aid of computational models or other analytical tools, the sociocultural phenomena we wish to discern from the data might still not be self-evident. Detection typically requires some further examination and interpretation of the analytic results. As Fricker, Buttrey, and Evans point out in their chapter, “Visualization for sociocultural signature detection,” visualization techniques provide invaluable support for this final step in discovering the sociocultural signatures associated with the data and identifying when those signatures change.

This chapter provides a broad overview of the most widely used approaches to visualizing data. The authors devote particular attention to the methods best suited for the data types relevant to the detection of sociocultural signatures: networks, geographic information, survey data, linguistic data, and social media data. While the methods discussed are applicable to the other operational capability areas (understanding, forecasting, and mitigation) as well, this chapter emphasizes how those capabilities are employed for detection. Accordingly, the discussion highlights exploratory data analysis, as well as simplifications that help focus attention on differences across a data collection or on changes in the data that occur over time.

Training

Sociocultural signatures must be interpreted in context. Consequently, detecting sociocultural signatures requires more than discovering indicators of sociocultural phenomena in data or in analytic results. It also demands a deep understanding of the real-world signatures associated with the findings in the data, why they are important, and what they mean. In "Cross-cultural training and education for detection," Glazer, Saner, Barnes, and Pavisic explain how sociocultural analysis can aid understanding of *how* and *why* the observed phenomena manifest themselves in a particular form in a given setting. They also point out the importance of cross-cultural training and education as prerequisites for conducting robust sociocultural analysis.

Knowledge about culture provides the context needed to achieve the level of sociocultural awareness required for detection. This chapter provides an overview of culture and culture-general concepts, reviews findings from state-of-the-art research on culture, and identifies gaps in current analytic practice. Glazer and colleagues also offer observations about implications regarding the most effective methods and designs to train and educate intelligence professionals to increase their sociocultural awareness.

As these brief descriptions show, analysts can apply a wide variety of methods and technologies to help them discover, distinguish, and locate sociocultural signatures. More work remains, however, to make these capabilities routinely available for operational use, and each chapter indicates some promising directions.

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5 Transforming data into information: Enabling detection and discovery for sociocultural analysis[1][2]

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1. Introduction

Nowadays it seems impossible to open any recent issue of a technical journal, trade newsletter, or popular science publication that does not contain at least one article about "big data." To be sure, digital data is accumulating at a staggering rate – roughly 80 petabytes an hour, more than 10 times larger than the holdings of the Library of Congress (Smolan & Erwitt, 2012). The combination of systematic data collection by commercial and government organizations, the emergence of unstructured digital data sources from news and social media, and advances in sensor technology has led to this explosion of data. For researchers seeking to detect interesting sociocultural patterns, the volume of data presents both opportunities and challenges. The opportunities stem from the availability of data to describe many aspects of the daily life of individuals and societies. The challenge is distilling this massive quantity of bits and bytes into meaningful information that supports deeper analysis.

In approaching the derivation of understanding from raw data, we present a conceptual framework that considers the basic processing components (Figure 1). The raw data can originate from any number of sources: surveys, social media, news reports, and sensor data. One can exploit each of the sources individually, but greater benefits often arise from synergistic analysis of multiple sources, i.e., information fusion (Hall, 1992; Klein, 1999). The timeline for developing inferences from the data depends on the specific mission or application. In some tactical settings users may need to derive inferences, including warnings or alerts, under demanding time constraints. Deeper analysis, including forensics, might require days, weeks, or even months. The ways in which users might interact with the analytic tools differ for these two types of missions.

1.1. Data Sources

Many sources of data provide useful information about sociocultural issues, either directly or indirectly. Traditional tools for social science research have included direct observations and surveys, as well as published media such as news reports. More recently, social media have changed the nature of the data, because now the actors in a society provide information directly

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rather than through the filter of an observer. Lastly, researchers are starting to explore sensor data, such as imagery that measures physical phenomena, as a source of information.

1.2. Sources to Evidence

Raw data generally have only limited value. Some processing is necessary to extract useful information from the original sources. The methods for transforming sources of raw data into information or evidence depend on both the nature of the source data and the information required by the end user. For example, processing the results of a survey to assess support for a political candidate can be simple. The tabulation of the responses gives an initial indication of findings, and more sophisticated processing would weight the responses in accordance with the sample design. Still more sophisticated analysis might attempt to assess the veracity of responses or impute values for missing responses based on answers to related questions (Cooley & Lohnes, 1971). More challenging data sources include unstructured and semi-structured text. For example, a researcher might want to explore the level of support in neighboring Arab states for the Syrian rebels seeking to overthrow President Assad by examining posts on social media sites. Turning the text data into relevant information involves performing sentiment analysis on relatively unstructured text that could include slang and country-specific references. This type of analysis presents far more challenges and the tools available today, while promising, are less than perfect.

Transforming data into information can also involve a data association problem. If multiple sources of data are available, which pieces go together? For example, one might find a photograph of a demonstration on Flickr and tweets about demonstrators being arrested. Are these two chunks of data related? Associating two data elements often relies on some co-occurrence in space and time. Reports that refer to the same location and date are likely to describe the same event. When such information is limited, estimation of these attributes is necessary and the data association carries a level of ambiguity. Other methods of data association might rely on named entities; for example, texts that refer to the same person or event might belong together.

1.3. Evidence to Inference

Armed with useful information, researchers must next draw inferences based on the data. Various inferences are possible, depending on the research questions and the nature of the data. Common types of inference include:

Discovery: Uncovering a new phenomenon or relationship. The researcher has access to information that has not been fully exploited and should have some working hypotheses, but the exploration of the data could reinforce or refute these hypotheses. More important, the exploration can suggest new relationships to consider. Data mining offers a set of tools commonly used for discovery.

Estimation and modeling: Determining the quantity, strength, or extent of a behavior, attribute, or relationship. One may want to estimate the size of a particular ethnic group, for example, or the relationship between religious affiliation and political party. Survey research provides a traditional tool for this type of analysis. The formulation and testing of models often accompany estimation. Consider, for example, the likelihood of a particular district voting for particular party in the next

election. A simple model might explore the relationship between party affiliation and other factors, such as ethnicity, religion, and income.

Change detection: Identifying a departure from past norms or behaviors. The ability to detect genuine changes in a society and to distinguish real changes from random fluctuations, is critical to identifying emerging patterns. Early detection of the Arab Spring, for example, could have benefited numerous decision makers by signaling the possibility of regime changes and the implications for trade, commerce, and diplomacy. However, many societies have experienced various levels of unrest without experiencing the changes of government that occurred in Tunisia or Egypt. What tools help us distinguish true changes from small perturbations in a society?

1.4. User Understanding

Researchers could perform the preceding steps in processing via automated methods, user manipulation of the data, or a combination of human and automated processing. The final step requires a human to interpret the results of the processing. Deeper analysis and understanding can only come when the user examines the inferences produced by processing, displaying, and visualizing the information, and explores the relationships. A separate chapter in the Detecting section of this book explores data visualization in more depth. For the purposes of the present discussion, however, it is important to realize that users need tools and methods for querying the data, displaying information, and understanding the data provenance.

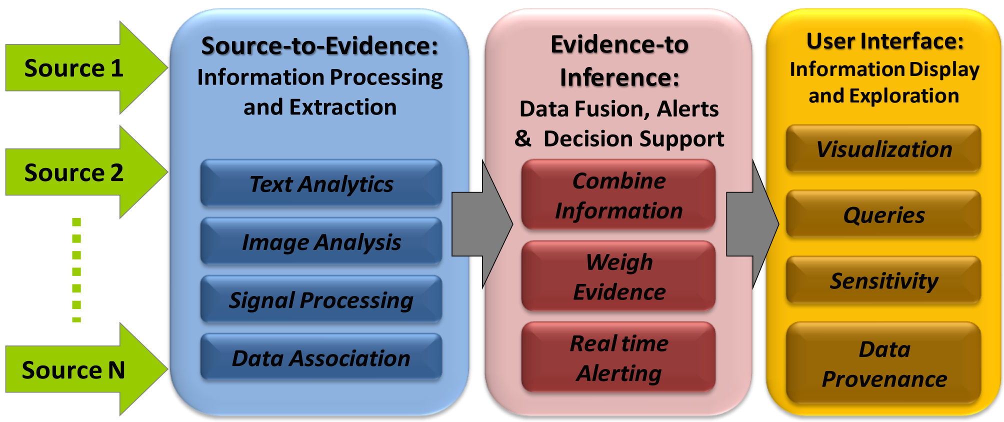


Figure 1. Processing steps for transforming data into actionable information.

Section 2 of this chapter focuses on the first portion of Figure 1, exploring several types of data relevant to sociocultural analysis and some of the methods for processing these data. Section 3 describes the development of inferences from the processed data, as portrayed in the middle box in the figure. Many methods support data analysis, fusion, and inference, but we concentrate on selected topics relevant to sociocultural modeling. The chapter concludes with some discussion of the technology gaps.

2. Data Sources and Information

Almost any source of data contains information, either direct or indirect, about the society and culture that produced the data. Certain data sources, however, have emerged as particularly useful for understanding sociocultural phenomena. In this chapter, we focus on four specific sources: survey data, social media, imagery data, and video data. Some of the data sources we discuss are also addressed in other chapters in this volume; in the present chapter we focus on the use of data and information for purposes directly related to detection.

2.1. Survey Data: Controlled Methods for Data Collection

A basic approach to understanding individuals and societies consists of asking them questions directly. A conversation with one individual is termed an interview. While interviews can be revealing, the information is specific to the person being interviewed. A broader discussion with multiple participants, in the form of a focus group, offers a systematic way to elicit a broader set of information. Extending the concept to a structured approach that elicits information from many respondents moves the process into the realm of survey research. Depending on the research questions, a trade-off exists between the rich narrative available from open-ended questions with free-text responses and specific, focused questions amenable to quantitative analysis.

Surveys have many advantages. They offer a direct measurement of attitudes and opinions, the methodology has a high degree of transparency and repeatability, the data acquired are amenable to analysis using standard statistical tools, and the results and findings can be represented quantitatively. Some of the drawbacks arise from the costs of conducting surveys, the challenges of designing good survey instruments, and the difficulty of performing surveys in some parts of the world. Not all respondents may feel comfortable giving honest responses to certain types of questions, either because of cultural norms or because of safety concerns. In some cases, researchers can devise questionnaires that address sensitive issues in ways that make the respondent more comfortable; in other cases, it may be impossible to obtain responses to certain questions. For example, in a country with a regime known for suppressing dissent, survey respondents are unlikely to give honest answers to questions about support for the government.

Numerous books and tutorials discuss methods for conducting surveys, and the use of survey methods has grown in recent years. Cross-cultural survey research requires particular care due to various methodological pitfalls (University of Michigan, 2011). A number of commercial organizations can provide the necessary services for anyone wishing to conduct a survey. Nevertheless, researchers must understand the process of designing and running the survey.

Research objectives: Identifying the research objectives is critical. What does the researcher want to learn about the society and its members? Is the research topic even amenable to survey methods?

Development of survey instruments: Designing the questionnaire is generally an iterative process. Questions mean different things to different people. Through testing and interviews, the researcher must refine the questions to ensure that responses will be informative. The willingness

of respondents is another important consideration. How much time does the survey take? Are respondents compensated for their time?

Translation and pilot testing: What language(s) do the respondents speak? In some countries, it may be necessary to conduct the survey in multiple languages. Are the questions asked of the different language groups comparable? Pilot testing of the survey instruments can help address this concern, but a fundamental understanding of the language issues is vital.

Sample design: Generally, surveys are conducted to make estimates about a particular society. Does the sample design for the survey reflect these objectives? For example, if the research covers the country as a whole, does the survey sample all geographic regions? Does it include a mix of urban and rural respondents? An extensive literature exists on sample design and weighted sampling units (Cochran, 1977; Thompson & Seber, 1996). In particular, methods exist for partitioning the population into strata and using different sampling rates for each stratum. Depending on the objective of the survey, these stratified sampling methods can be cost-effective methods for conducting the research.

Data collection: The actual field work of conducting the survey is labor intensive. Depending on the region of the world, safety of the interviewers, the costs of the operation, and the difficulty in obtaining complete responses pose varying types of challenges.

Data cleaning: Respondents often do not answer all of the questions posed by the interviewer. In addition, the type of question can introduce ambiguity in the responses, especially if open responses (rather than pre-coded answers) are allowed. The data cleaning step verifies the quality and correctness of the information and assigns appropriate codes for missing responses.

Unstructured data: Open-ended survey questions and focus group discussions can generate a large amount of useful information, but the data are generally captured as unstructured text. These data can be analyzed through the labor-intensive process of reviewing all of the free text to identify useful information. Alternatively, researchers can employ automated text analytics to extract content, identify entities, or analyze sentiment. While these automated methods can prove cost effective for processing large volumes of data, they contain some inherent level of error.

Data analysis: Well-developed statistical methods exist for analyzing data. The responses to survey question are frequently captured as Yes/No or multiple choice responses. Researchers can use methods for categorical data analysis, including log-linear modeling, to analyze individual questions and relationships across questions (Agresti, 2012).

Generalizing from the survey: The goal of survey research is to develop an understanding that extends to a larger population. The validity of this generalization depends on the sampling method used to obtain survey responses. If the research uses stratified sample methods, estimated rates, confidence intervals, and tests of hypotheses must be handled appropriately (Fay, 1990; Wolter, 1985).

Well-designed surveys can provide tremendous insights into a society. One example is an extensive set of public opinion data collected in sub-Saharan Africa over several years under the Afrobarometer Program. The Afrobarometer is a collaborative enterprise of the Centre for Democratic Development in Ghana, the Institute for Democracy in South Africa, and the Institute for Empirical Research in Political Economy with support from Michigan State University and the University of Cape Town, Center of Social Science Research. Each Afrobarometer survey collects data about individual attitudes and behavior, including indicators relevant to developing societies. These issues are summarized in Table 1.

Table 1. *Issues addressed in Afrobarometer surveys*

Topic Area	**Description**
Democracy	Popular understanding of, support for, and satisfaction with democracy, as well as any desire to return to, or experiment with, authoritarian alternatives.
Governance	The demand for, and satisfaction with, effective, accountable and clean government; judgments of overall governance performance and social service delivery.
Livelihoods	How do families survive? What variety of formal and informal means do they use to gain access to food, shelter, water, health, employment and money?
Macroeconomics and Markets	Citizen understandings of market principles and market reforms and their assessments of economic conditions and government performance at economic management.
Social Capital	Whom do people trust? To what extent do they rely on informal networks and associations? What are their evaluations of the trustworthiness of various institutions?
Conflict and Crime	How safe do people feel? What has been their experience with crime and violence?
Participation	The extent to which ordinary people join in development efforts, comply with the laws of the land, vote in elections, contact elected representatives, and engage in protest. The quality of electoral representation.
National Identity	How do people see themselves in relation to ethnic and class identities? Does a shared sense of national identity exist?

The survey data provide a rich portrait of societal attitudes across several countries and multiple regions within each country. For some countries, surveys have been repeated over multiple years, giving a temporal characterization of shifting attitudes and opinions. For instance, one survey question explored attitudes concerning the importance of having a democratic society and the freedom to criticize the government. Responses show distinct patterns by country and, to a lesser extent, within countries (Figure 2). Deeper analysis reveals that within a country, attitudes vary with the level of urbanization and the economic status of respondents.

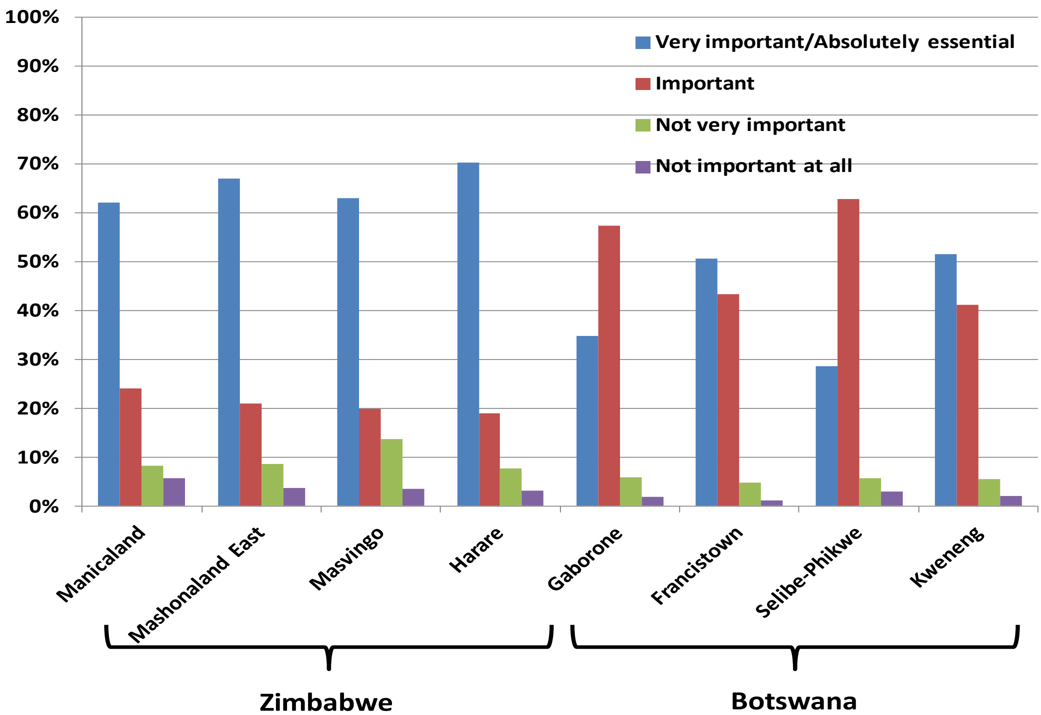


Figure 2. Democratic society and freedom to criticize the government. Responses by country and region from Afrobarometer data (Afrobarometer, 2013).

2.2. Social Media: Text and Multimedia Data

The use of social media has exploded in recent years, making multiple sources of data available to anyone who can harvest all the bits and bytes. Analysis of social media data appeals for several reasons: it provides direct access to people's comments and opinions, the information is readily available, and very little time elapses between the unfolding of an event and the corresponding reactions in social media. Because social media offer direct links to events as they happen, numerous researchers are exploring ways to leverage this data for understanding a wide range of geopolitical, economic, and sociocultural issues.

The data sources include exchanges of short text messages (such as Twitter); longer unstructured text messages that appear on Facebook, blogs, and other sites; and imagery data uploaded to sites

such as Flickr and YouTube. Many of the popular sites are specific to a single country or limited geographical region. For example, people in China have no access to Facebook, Twitter, and YouTube. Instead, Weibo, Renren, Youku, and Kaixin fill the niche. In addition, the information posted to social media sites can be in a variety of languages, including slang or common shorthand terms that members of the online community know and use. Methods for information extraction must be designed and tuned accordingly (Bollen, Mao, & Pepe, 2011).

Automated methods for extracting useful information from these sources must address a number of issues: access to the data, data volume, language, and the unstructured nature of the data. A growing body of research explores methods of analysis for unstructured and semi-structured text. Some of the technical challenges include automated methods for entity and topic identification, content extraction, sentiment analysis, and trend analysis (Feldman & Sanger, 2006; Manning & Schuetze, 1999).

One interesting area of investigation combines the content analysis of social media with geospatial data. Along with the actual content of tweets, blog posts, and images on Flickr, the metadata often include location information. Combining this location information with simple content analysis can reveal patterns of spatial distribution and movement. Since many people use mobile devices, such as smart phones, even rapidly changing events have become amenable to geospatial analysis through social media. An interesting example (Stefanidis, 2013) depicts the spatial analysis of Twitter data related to the rebel activity in Syria (Figure 3). As expected, the heat map shows intense activity in Syria and high levels in surrounding countries in the Middle East. Looking globally, however, we see pockets of activity in North America and Europe, as well as smaller hot spots in Argentina and Australia. This suggests active Syrian communities or supporters in specific parts of the world outside of Syria. Researchers can now perform deeper analysis of the content and related data sources to understand the nature of these communities.

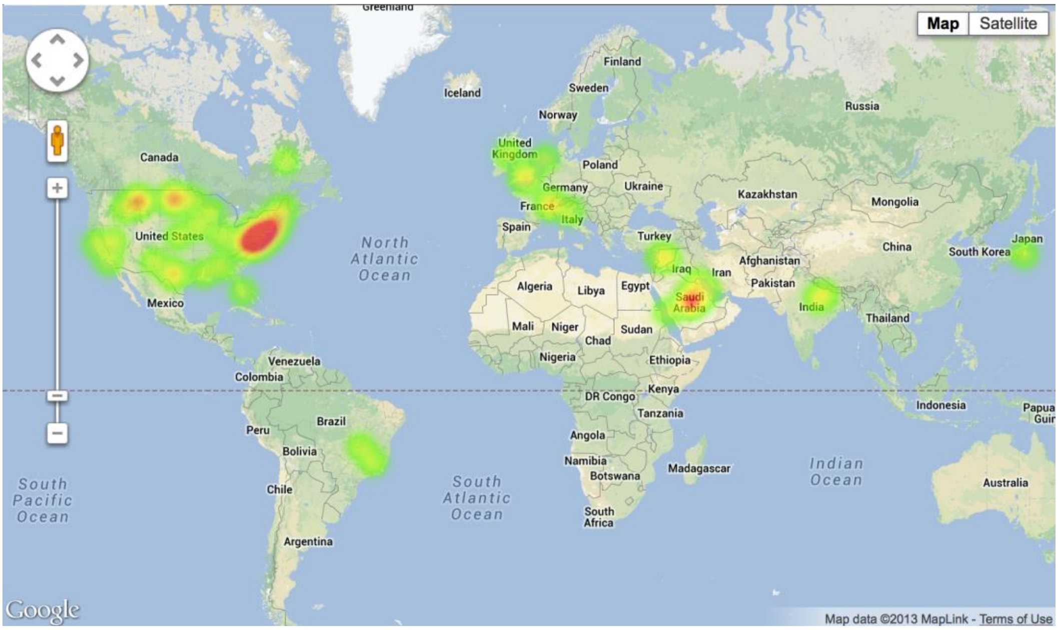


Figure 3. Social media map of the Syrian community. Adapted with permission from Stefanidis (2013).

Exploiting social media data represents a fundamental change in data acquisition and analysis. Other methods for data collection, such as surveys or sensor-based methods, rely on designed data collection plans for obtaining the information. Collection of social media is entirely opportunistic: the target populations generate the data through their normal activities and the researcher can harvest this information for subsequent analysis. With traditional methods, the target population and the data acquisition process are distinct. With social media, the objects of study are also the source of the data. In effect, members of the target population also function as the "sensor."

Social media offer a number of advantages over traditional data sources. Because the data acquisition process is built into the society, no separate observation process, such as conducting a survey or flying a sensor, is necessary. Thus, acquiring social media data can be much less expensive than other methods. Furthermore, social media offer a direct method of observation; attitudes and opinions can be captured without any of the filtering or interpretation inherent in other methods. Lastly, the data source can be extremely timely. Participants in an event often tweet immediately, enabling researchers to observe events in near-real time.

Despite these advantages, analyzing social media data involves some serious challenges. The first stems from the nature of the data. Observations are largely unstructured and each small packet of data, such as a tweet or a blog post, contains very little information. The power of this data source rests in the accumulation of evidence across a large set of observations. Therein lies the challenge. The research must harvest the data and process it in a way that sifts out the meaningful content from the morass of data. Some social media data include metadata, such as time and location tags,

that can assist in this process. However, researchers must extract content, entities, and sentiment from unstructured text to realize most of the benefits of these sources.

Another limitation of social media data is the inherent sampling bias in this source. The people who use social media are generally younger, better educated, and technologically savvy. They have access to computers, smart phones, and iPads and are more likely to live in or close to urban areas. Consequently, observations drawn from this source probably under-represent older generations, residents of rural areas, or the poor. Despite these limitations, however, social media offer an exciting new window into the attitudes and workings of a society.

2.3. Sensor Data: Imagery

The application of remote sensing and geographic information systems (GIS) to the social sciences is an emerging research area (Blumberg & Jacobson, 1997; Crews & Walsh, 2009; Goodchild, Anselin, Appelbaum, & Harthorn, 2000; Taubenbock et al., 2009). “Remote sensing can provide measures for a number of variables associated with human activity—particularly regarding the environmental consequences of various social, economic, and demographic processes” (National Research Council, 1998, p. 116). Recognizing that people’s behavior and values shape, and are shaped by, the environment in which they live, researchers have explored a number of issues, including sociocultural and economic attributes of the population, ethnography, and land use (Fox, 2003; Jiang, 2003). A review of the literature indicates that investigators are exploring the connection between remote sensing and social science issues. Established research focuses on urban studies, demography, archaeology, land use and land cover, and war and conflict studies (Hall, 2010). Recent and emerging areas of investigation include deeper exploration of economic and governmental attributes.

Several recent studies have demonstrated that imagery collected from space-based or airborne imaging assets can reveal useful information about societies and the environment in which they live. The LandScan Project at Oak Ridge National Laboratory has developed methods for estimating populations and population distribution on a global basis (Landscan, 2013; Bhaduri, Bright, Coleman, & Urban, 2007; Cheriyadat, Bright, Bhaduri, & Potere, 2007; Vijayaraj, Bright, & Bhaduri, 2007; Vijayaraj, Cheriyadat, Sallee, Colder, Vatsavai, Bright, & Bhaduri, 2008). This program has demonstrated the practical application of remote sensing methods for mapping human settlements and analyzing population movements over time. A recent study of the urban landscape in Guatemala (Owen, 2012) represents a more focused application of remote sensing. This work made an important contribution through an assessment that distinguished informal (slum) and formal (planned) settlements using high-resolution imagery. Finally, Min made a novel use of “nightlights”[3] data to assess political and military activity remotely (Min, 2008a).

[3] Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) captures night imagery of the earth, which can reveal lighting patterns arising from human settlements.

Table 2. *Research issues and potential observables to explore*

Research Issue	**Potential Observables**
Income and Economic Development:	House sizes: average size, range of sizes Presence of motor vehicles Physical infrastructure Agriculture: extent and mix of cultivation, crop health, presence and extent of livestock
Centrality and Decision Authority	Road network; lines of communication Physical infrastructure (bridges, paved roads, schools, mosques)
Social Capital	Community infrastructure and prevalence of meeting places and institutions (schools, places of worship). Communications infrastructure (roads)

Social science research suggests several ways in which local attitudes and behaviors may correspond to phenomena observable in overhead imagery. Although this set is not exhaustive, certain issues have a foundation in social science research and a logical connection to observable phenomena (Table 2). The theory suggests natural hypotheses to examine in three areas: income and economic development, centrality and decision authority, and social capital. First, overhead imagery reveals numerous indicators of economic status (housing, vehicles, crop land, livestock, and infrastructure). Studies have explored the relationship between remote sensing data and the economy (Elvidge, Baugh, Kihn, Kroehl, Davis, & Davis, 1997; Irvine et al., 2013). Second, both higher income and equitable distribution of income are associated with good governance. Observables associated with economic well-being, including measures of wealth distribution, also serve as relevant indicators of governance. The transportation and communication infrastructure provides indicators of expected levels of social interactions. Third, high social capital has been linked to good governance (Bardhan, Bowles, & Gintis, 2000; Bowles & Gintis, 2002), but observing meaningful measures that correlate with social capital poses a challenge. Evidence of economic growth can be associated with higher levels of social capital (Knack & Keefer, 1997). Although social cohesion and connectedness cannot be measured directly, durable institutions (e.g., schools, places of worship) and infrastructure (e.g. roads, cell towers) are indirect indicators of social connectedness.

Cultural, social, and economic factors critical to understanding societal attitudes are associated with specific phenomena observable from overhead imagery. Distinguishing among industrial,

commercial, and residential areas, for example, is a standard use for imagery (Harvey, et al., 2002; Harvey, McGlone, McKeown, & Irvine, 2004; Jenson & Cowan, 1999; O'Brien & Irvine, 2004). Researchers can also extract measures of socioeconomic status (e.g., house size, crop area and crop vigor, presence of vehicles) from high-quality imagery. Other factors may also be inferred from indicators derived from the imagery such as population density, access to improved roads, distances to commercial and governmental centers, and attributes of communities. Patterns that emerge from the correlation of the geospatial analysis with survey data can suggest phenomena observable in imagery that serve as reasonable surrogates for the direct measurements of public opinion (Irvine, Regan, & Lepanto, 2012; Irvine, Lepanto, Regan, & Young, 2012). Researchers can apply various image processing techniques to extract and identify specific indicators from the imagery (Table 3).

Table 3. *Illustrative imagery observables and derived indicators*

Feature Class	**Observables**	**Derived Features**
Land Cover	Arable land Area under cultivation Crop health	Level of commercial agriculture Expected food supply
Buildings	Sizes of buildings Number of types of buildings Size of residential buildings Presence of a "large" building	Degree of urbanization or industrialization Population density and distribution Average size of residential buildings Indication of a mosque, school, or community building
Lines of Communication	Road network (paved and unimproved) Other transportation Numbers and types of vehicles Distance from major commercial centers	Level of communication Infrastructure to support local commerce Access to transportation

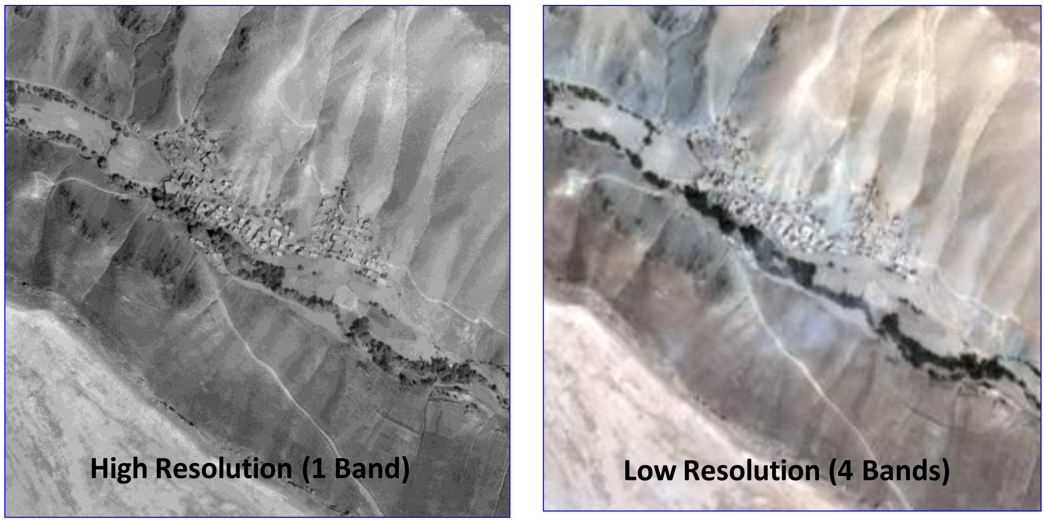


Figure 4. Illustrative panchromatic and multispectral imagery of one village in Afghanistan.

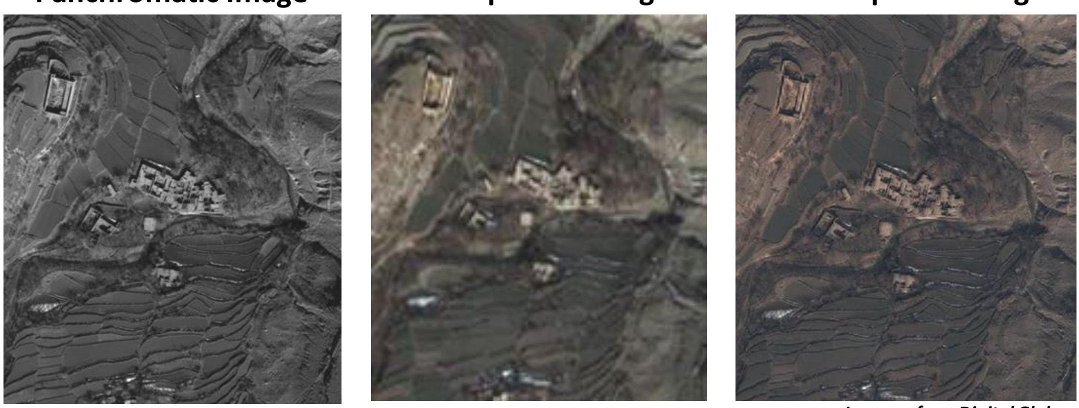
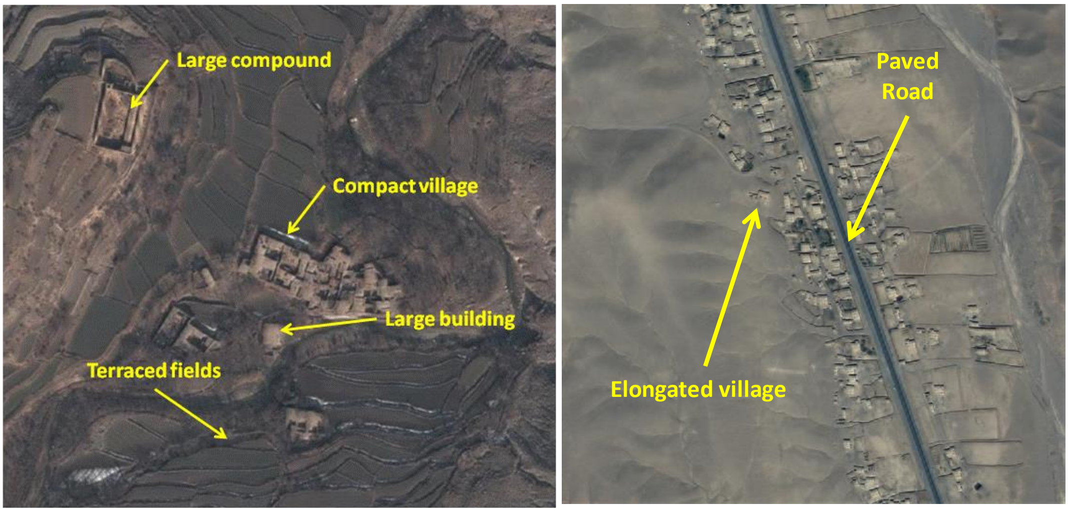


Figure 5. Panchromatic and multispectral images chips with the pan-sharpened product.

To illustrate, we present analysis of commercial panchromatic and multispectral satellite imagery collected over northern Afghanistan (Figure 4). The panchromatic imagery, having finer spatial resolution, can reveal details about the shapes of objects. The multispectral imagery has coarser resolution, but includes data in four spectral regions (red, green, blue, and near-infrared). This

spectral information can reveal material properties, such as the types of roads, buildings, crops, and vegetation. Panchromatic sharpening (Alparone, Wald, Chanussot, Bruce, & Thomas, 2007; Lee & Lee, 2010) can combine the two images to produce a fine-resolution multispectral image (Figure 5).



Imagery from Digital Globe
Provided by NGA

Figure 6. Illustrative features evident for each village.

An extensive literature addresses methods for extracting features from remotely sensed imagery (Campbell, 1987; Lillesand & Kiefer, 1994). Analysis of the imagery in this example leveraged both spatial and spectral information to identify features of interest. The specific features extracted from the imagery include estimates of the number of buildings, building sizes, building density, extent, and health of crops, and types of roads (Figure 6). Derived features also quantified the size, shape, and density of each village. To supplement the automated processing, visual inspection of the imagery produced ratings of relevant characteristics. Comparison of the computed features to ground truth or observer-generated data is useful for assessing the performance of the automated methods (Irvine et al., 2013).

As shown in Figure 7, automated processing of the pan-sharpened imagery employed a mix of spectral and spatial attributes to extract features of interest (Irvine et al., 2013). The four-band multispectral data offers information about material type. Spectral analysis shows that the material properties of the buildings differ from the surrounding spectral signatures. Using the spectral signature, we identified regions as buildings, crops, trees, or "other." Spatial analysis considered edge features. For example, the villages typically consist of a number of closely spaced buildings that give rise to many edges in the panchromatic scene. Regions of high edge density correspond to the spatial extent of the village. Merging the spatial and spectral information yields detection of the individual buildings. From these detections, we compute the number of buildings, building sizes, and building density. The vegetation and crop analysis begins with identification of the crop

land based on spectral features. To assess crop health, we use the computed normalized difference vegetation index, which indicates the presence and health of vegetation (Kriegler, Malila, Nalepka, & Richardson, 1969).

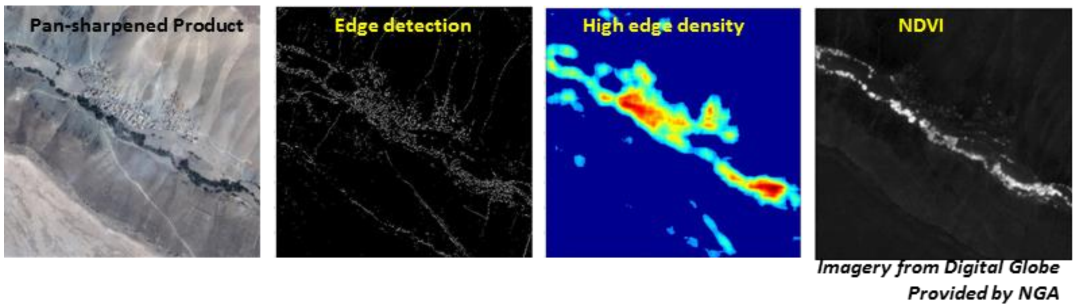


Figure 7. Image processing to identify built-up areas comprising a village.

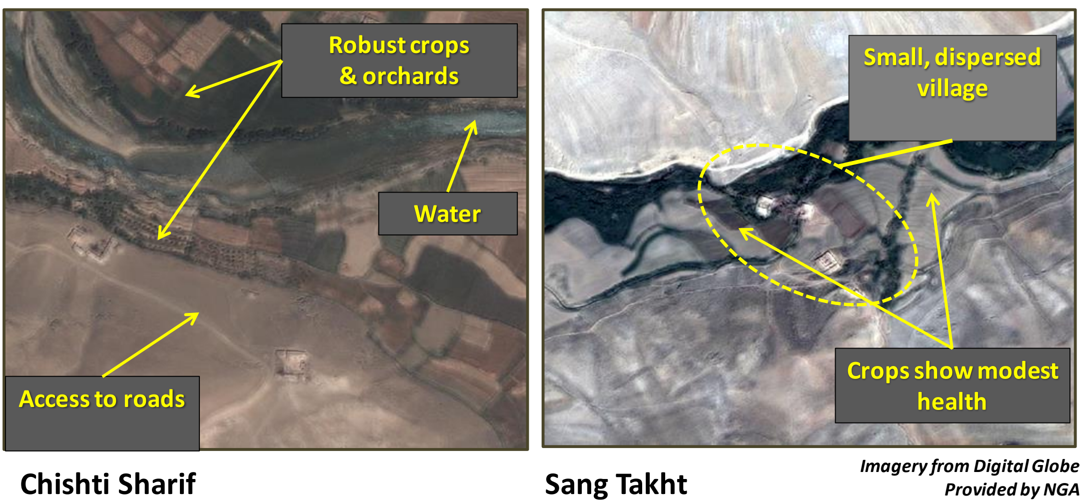


Figure 8. Imagery data can provide reliable estimates of key sociocultural dynamics.

Imagery of one town in Chishti Sharif shows that crops are robust and the town has access to water and good road transportation (Figure 8). By contrast, a village in Sang Takht shows a dispersed building infrastructure and lower crop vigor. These factors indicate the economic health of the two villages. When compared to ground observations, the imagery-based analysis accurately predicts the economic health of the villages. If the crops are healthy and the village has good access to other resources, the likelihood is high that the economic conditions are relatively strong.

2.4. Sensor Data: Video Imagery

Many recent discussions talk about "patterns of life"—the normal activities of an individual or group. The patterns of life that define normal activities are inherently specific to a society. These patterns depend on cultural norms of behavior, economic structure and incentives, and the physical environment. For example, an activity of interest could pertain to the behavior of people in a commercial area, such as an open-air market. Is it normal for people to shop in groups or individually? Do people linger and socialize? Difference in gender roles (Jain, 1985) and age structure of the population (Baltes, Wahl, & Schmid-Furstoss, 1990) affect the behavioral norms.

If it were possible to model normal activity, could potential threats or concerns be discovered as departures from normalcy? Analysis of activity requires temporal understanding. The static imagery discussed in the previous section captures a snapshot in time, but understanding more dynamic phenomena requires repeated observations over time—a process to which video imagery is ideally suited.

Video data provides the capability to analyze temporal events, which enables far deeper analysis than is possible with still imagery. At the primitive level, analysis of still imagery depends on the static detection, recognition, and characterization of objects, such as people or vehicles. By adding the temporal dimension, video data reveals information about the movement of objects, including changes in pose and position and changes in the spatial configuration of objects. This additional information can support the recognition of basic activities, associations among objects, and analysis of complex behavior.

The information complexity associated with analysis of a target object has a natural hierarchy. The progressive stages of processing appear in Figure 9, where successive components indicate the decreasing maturity of current methods. The first two components on the left exploit information in the sensor phenomenology domain, while the two components on the right exploit extracted features derived from the sensor data.

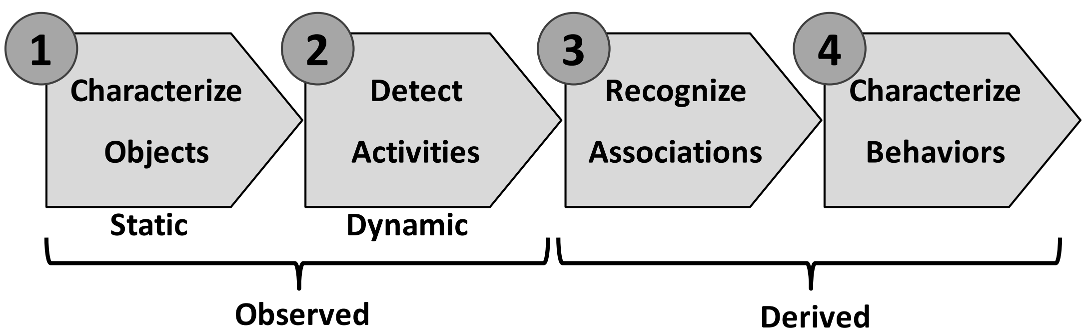


Figure 9. Levels of exploitation for motion imagery data.

To illustrate the concept, consider a security application with a surveillance camera overlooking a bank parking lot. If the bank is robbed, a camera that collects still images might acquire an image depicting the robbers exiting the building and show several cars in the parking lot. The perpetrators have been detected (stage 1 in the figure), but additional information is limited. A video camera might collect a clip showing the same people entering a specific vehicle for their getaway. Now both the perpetrators and the vehicle have been identified because the activity (a getaway) was observed. This is the second stage of understanding, which requires acquisition of temporal information to recognize an activity. Moving to stage 3, we consider relationships among information acquired in multiple times and places. If other security cameras throughout the city detect the vehicle in our example, analysis of multiple videos could reveal the pattern of movement and suggest the location of the robbers' base of operations. In this way, observers can form an association between the event and specific locations, namely the bank and the robbers' hideout. If the same perpetrators were observed over several bank robberies, one could discern their pattern of behavior, i.e., their *modus operandi*. Thus, the fourth and final level of processing examines a corpus of data to assess patterns of activities and associations. This information could enable law enforcement to anticipate future events and respond appropriately (Gualdi, Prati, & Cucchiara, 2008; Porter, Fraser, & Hush, 2010).

Methods for recognizing activities in video data encompass a multistep process that begins with tracking objects, such as people or vehicles, in the video data (McPherson, Irvine, Young, & Stefanidis, 2012). By analyzing the speeds and trajectories of these objects and their relations to other objects, we can infer some understanding of behaviors. For example, one person stationary on a sidewalk may be *loitering*, but another person approaching him represents a *meeting*. Researchers have developed methods for analyzing the kinematics to infer primitive activities and construct an understanding of complex activities.

Several standard methods can perform the first stage of processing—converting raw video frames into object tracks (Beymer, McLaughlin, Coifman, & Malik, 1997; Regazzoni, Fabri, & Vernazza, 1999). This video conversion step is the only process that references the raw video directly. Subsequent processing depends on the object positions and velocities (i.e., the kinematics). This approach is sensor agnostic in that multiple sensors could provide suitable object track data and the activity analysis can combine and compare information across the sensor types. For example, information from full motion video could be combined with information derived from wide-area motion imagery or ground moving target indicator data. The fundamental requirement is that the data source has sufficient data quality to support accurate information extraction (McPherson et al., 2012; Wood, McPherson, & Irvine, 2012). Simple activities include a person walking, running, standing close to a car, or approaching another person, vehicles stopping at particular locations, etc. (Table 4). Complex activities are linearly ordered time sequences of simple behaviors (e.g., persons interacting by conversing or exchanging a package, and vehicles traveling in convoy or making a rendezvous) (Figure 10).

Table 4. *Processing levels for representation of complex activities*

Semantic Level of Activity	**Example of Activities**	**Analytic Methods**
Level 1 activities (atomic level)	Meet, enter, exit, loiter	Tokenization
Level 2 activities (interaction of tracks)	Attraction (location where moving objects pause, before continuing) Pick-up / drop-off Mount / dismount (enter/exit mover) Portal (enter stationary object)	Recognition by syntactic methods
Level 3 activities (interaction of level 1 and 2 activities)	Object hand-off (drop-off, pick-up) Tribal elder (many meetings by relatively stationary person) Bury IED (exit vehicle, move, loiter, move, enter vehicle)	Recognition by syntactic methods

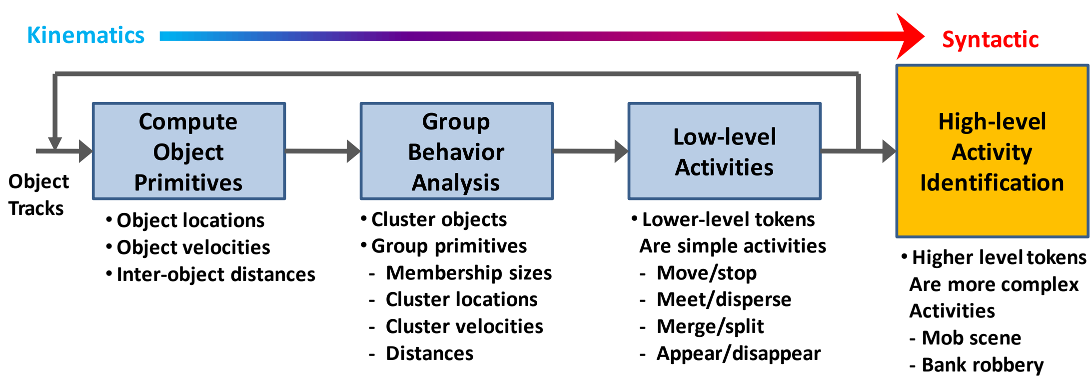


Figure 10. Overview of syntactic data processing method.

Once object positions and tracks are extracted from the video data, the second layer of processing tokenizes the track data (i.e., converts short increments of track data into a symbolic representation) according to a finite set of tokens based on position, velocity, and time. This tokenization step yields a compact, symbolic representation of information on entities in a form appropriate for syntactic recognition. Researchers have explored different techniques for this tokenization. One approach is a geometrically invariant kinematic analysis, which employs heuristics to characterize tracks in space and time and the relationships among entities in space-time. An alternative approach applies a clustering method to the track data to discover atomic elements. Subsequent analysis rests on syntactic methods for string representations of these elements.

In general, real-world activities are semantically complex. Recognizing behaviors requires the ability to build discriminative models that generalize across missions. Representing simple behaviors using symbols or “tokens,” as described above, facilitates pattern discovery. The time sequence of simple activities is represented as a string of symbols. Researchers can discover the recurring patterns in simple behaviors through linguistic processing techniques that operate on the symbol strings. The symbols constitute the “alphabet” for encoding activity patterns. Frequent patterns constitute normalcy. Statistically improbable or unique patterns would be flagged as anomalies, i.e., possible activities of interest.

When the underlying behavior sequence contains noise and stochastic variation (which is common for activities involving humans), “tolerant” pattern discovery that finds approximate matches is required to ensure detection of all activities. The Fast Approximate Sub-tree Matching (FASM) technique (Deutsch, Kolacinski, & Peli, 2010) generates a prefix tree from the symbol stream, converts this structure to graph-invariant canonical strings, and finds all patterns and their frequency. The number of nodes is a function of the size of the symbol alphabet, the number of distinct activity patterns, and the maximum pattern size under investigation. FASM discovers approximate matches by calculating the edit distance[4] between canonical strings and by exploiting the bounding properties of the edit distance to accelerate the process.

Anthropologists learn about the culture of another society through first-hand observation in that society, i.e., ethnographic studies. Because culture primarily relates to the way people interact, researchers cannot observe it adequately in a laboratory setting. The systematic observation of activities from video imagery provides a limited type of ethnographic glimpse into a society. The movement and associations of people and vehicles reveal normal patterns of activity for the society. A subject matter expert in a particular society could suggest patterns that analysts could anticipate. By processing and analyzing sensor data collected over a particular region, the patterns that comprise the cultural model can be learned over time.

Cultural differences in normal activities can be derived from a comparison of models for two cultures. Thus, within the framework of activities defined by symbolic representations of movements of people and vehicles, a comparison of two normalcy models provides a type of ethnology for understanding the differences in behavior between two cultures. As an example, for the counterinsurgency mission this type of analysis could reveal the differences in behavior between, say, Iraq and Afghanistan. The model developed for one region (and its ability to detect anomalous behavior) may not translate immediately to a new region.

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[4] The *edit distance* (also called the Levenshtein distance) between two strings of characters is the minimum number of single-character edits (insertion, deletion, substitution) required to change one string into the other.

3. Inference and Analysis

Numerous issues arise in the analysis of the various information sources discussed in the previous section. In many cases, standard methods exist for conducting the appropriate analysis. For example, many books have been written about statistical methods, pattern recognition, data mining, natural language processing, and related topics. However, several new themes have emerged in recent years that merit greater attention. Two themes we address here are the use of network modeling and the detection of changes over time. Sociocultural analysis must recognize that the actors are individuals and groups that have relations with other actors. Graph representations of these relationships provide a powerful set of mathematical tools for understanding and modeling these relationships. Analytic methods for change detection provide a method for discerning when and how events and relationships shift over time.

3.1. Discovering and Analyzing Relationships

Social network models offer a rich mathematical framework for analyzing interactions among agents, whether individuals and/or groups of individuals. In a social network model, agents are represented by nodes in a graph and the relationships among agents by edges (arcs) in the graph. Depending on the application, the agents could be single individuals or specific groups of people that can be modeled as a single entity. In some cases, nodes may represent locations of interest, rather than actors, and the edges may represent routes connecting these locations.

Many sources of data can be used to discover or estimate the elements and structure of the network. Research has demonstrated construction of social networks from text (Carley, 1997) and social media (Carley, 2002). Multiple tools have been developed for analysis of networks (D'Andrea, 2010; Freeman, 2006; Newman, Barabasi, & Watts, 2006; Pfeffer & Carley, 2012; Wasserman & Faust, 1994) and new tools are being applied specifically to support military missions (Mathieu, Lorber, Ounanian, Fulk, Troop, & Bornmann, 2012). The field is far too extensive to describe here; rather, we explore two practical issues in the analysis of networks.

3.1.1. Incomplete view of the network

Ideally, it would be possible to observe all of the nodes and edges and achieve a complete understanding of the network. In practice, researchers must usually construct inferences from limited observations. One natural topic to consider is the completeness of the observations of the network. Do the available data represent most of the network or are we only seeing the tip of the iceberg?

We illustrate this problem using synthetic data that represent a small network aimed at the production and emplacement of improvised explosive devices (IEDs). A limited picture of such a network could emerge from analysis of data on the movements of network members drawn from motion imagery or other data sources.

Consider a simplified, hypothetical example application of network analytics, in which a small IED network consists of 15 nodes, corresponding to locations involved in the planning, manufacture, and execution of IED attacks (Figure 11). This network has three sub-networks corresponding to the planning, manufacturing, and execution aspects of the IED process. Each sub-network shows high

internal connectivity but limited connection to the other sub-networks. Analysis of a large set of track data derived from motion imagery could, in principle, reveal the network by observing the connections among the locations associated with each node. Figure 11, Panel B represents the true network as a directed graph. A Monte Carlo simulation of the tracks in this network generated 1,000 tracks that yield the estimated network in Figure 11, Panel C. The small difference between the true and estimated networks indicates a good estimate of the network. In reality, inferences about the network would be subject to noisy data, spurious nodes and links, limited observations, and changes in networks over time.

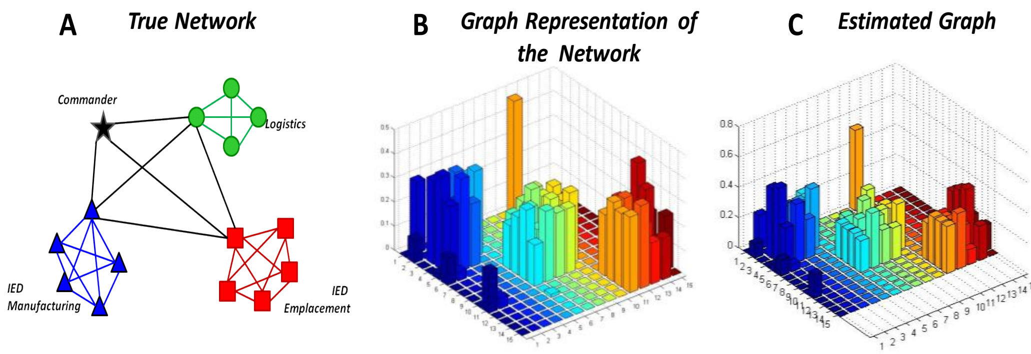


Figure 11. Simple example of an IED network. Panel A shows the simplified network, consisting of three sub-networks. Panel B is a graph-based representation, where nodes correspond to rows and columns, and the height of the bar is the strength of the edge between the two. Panel C is an estimate of the graph from a large sample of observations.

Network fidelity analysis uses computer-intensive capture-recapture methods to assess how well the current model represents the actual network. Limited data may give a very incomplete picture of the true network. Therefore, the method is based on a statistical technique called capture-recapture, which estimates how much of the network has been observed. The technique uses two samples of network data. Capture-recapture analysis (Cormack, 1989) compares the nodes that arise in both samples to the nodes that appear in only one sample to estimate the number of nodes that appeared in *neither* sample, i.e., the unobserved portion of the network. In our simple example (Figure 12), even though only 12 nodes appear in at least one of the samples, and only 8 nodes appear in both, the estimated total number of nodes is 14.67, remarkably close to the true value of 15.

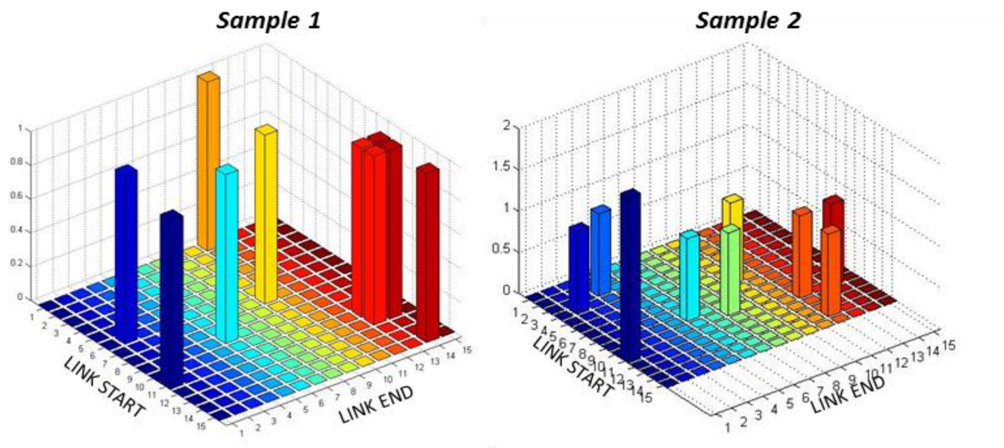


Figure 12. Two estimates of the directed graph from Figure 11, each estimated from 10 tracks. Note that the two independent estimates reveal substantially different views of the network.

In practice, the two samples can be constructed by partitioning a large data set. For a given set of data, the partition into two "samples" can be arbitrary. A computer-intensive resampling method for randomly partitioning the data and repeating the capture-recapture analysis can be used to construct both the point estimate and a confidence interval. Applying this technique to our simple example yields a final estimate of 14.89 nodes and a 95% confidence interval of 13.7 to 16.1. This technique can also be applied to the edges of the graph to assess our understanding of the relationships within the network. Additional discussion of capture-recapture methods appear in the text box.

Capture-Recapture Methods

Capture-recapture is a statistical technique originally developed for estimating populations in the wild. Imagine that you wish to estimate the number of fish in a pond. Suppose you capture 100 fish, tag them, and release them. A short time later, you capture another 100 fish. Suppose 10 of the fish in this second set had tags. Because 10 out of 100 fish were tagged in the second sample, we estimate that tagged fish represent approximately 10 percent of the population. But we know the total number of tagged fish, because that was the first sample of 100 fish. Hence, we estimate the total population to be approximately 1,000.

The method derives its name from the two-stage sampling process. Stage one (the “capture”) determines the tagged population and stage two (the “recapture”) assesses the proportion of the total population tagged. The techniques have been widely used in wildlife and ecology studies. More recently, the methods have been applied to estimating prevalence of disease.

To demonstrate the details, consider the two samples as portrayed in the table below. N_1 is the total observed from sample 1 and N_2 is the total from sample 2. We denote the number common to both by $n_{1,1}$. Hence $n_{1,0}$ is the number in sample 1 that were not in sample 2; similarly, $n_{0,1}$ is the number in sample 2 that were not in sample 1. The number not observed in any sample is $n_{0,0}$, and this is the value we need to infer.

		Sample 2		
		Observed	Not Observed	Total
Sample 1	Observed	$n_{1,1}$	$n_{1,0}$	N_1
	Not Observed	$n_{0,1}$	$n_{0,0}$	
	TOTAL	N_2		N

The capture-recapture estimate for the total population is:

$$N = (n_{1,1} + n_{1,0})\,(n_{1,1} + n_{0,1}) \,/\, n_{1,1} = (N_1)(N_2) \,/\, n_{1,1}$$

Capture-Recapture Methods *continued*

and the number of unobserved elements is:

$$n_{0,0} = N - N_1 - N_2 + n_{1,1}$$

The capture-recapture methods rely on simple principles of sampling. The method assumes that both samples were drawn randomly from the population. The method also assumes an open mixing of the population, such that the proportion of tagged elements in the second sample indicates the proportion in the population. For some practical applications, the sampling methods may depend more on the methods for acquiring the data. In the network application, different sources of information may sample certain regions disproportionately, leading to systematic differences in the sampling processes. In this case, extensions of capture-recapture to stratified samples and other complex sampling strategies has been an active area of research.

Furthermore, we assume that elements common to both samples can be easily identified. Again, this can be a problem for some applications. Suppose that one were studying a network formed by people contacting each other through phone calls. A call from one phone to another provides evidence of an edge linking the two nodes. If one source of data identified the nodes by the phone number and another identified them by name, recognizing which nodes were common to the two lists would require additional information.

3.1.2. Network modeling influence

Social network models indicate the connections and relationships among the actors. Simple models capture the relationship between two nodes as an edge or link that connects them. More complex relationships can be portrayed by assigning attributes to these links, including directionality. A network model of an organization, for example, could represent the authority structure as a directed graph to indicate a supervisory relationship between two nodes. A similar approach can be used to model the propagation of influence within a network.

We present a simple social network influence model to illustrate the possibilities. The starting point for this is a Markovian model developed by Acemoglu (Acemoglu & Parandeh, 2009; Acemoglu & Ozdaglar, 2010; Acemoglu, Como, Fagnani, & Ozdaglar, 2013; Acemoglu, Bimpikis, & Ozdaglar, 2014). The model represents the agents as nodes in the network graph. Values at each node indicate the attitudes of the respective agent and the edges of the graph represent connections among the agents over which influence occurs. The level of influence an agent (node) exerts on other agents (nodes) is modeled by the degree of forcefulness of each. The technique has been

applied to modeling influence in a village society, such as rural Afghanistan (Hung, Kolitz, & Ozdaglar, 2011; Hung & Kolitz, 2011; Hung, Kolitz, & Ozdaglar, 2013). Figure 13 illustrates a simple example of three villages, with the color of a node representing the value; i.e., a measure of the attitude of the agent, where 0.5 is "good/Blue," i.e., most positive attitude toward the Coalition Forces and –0.5 is "bad/Red," i.e., most positive toward the Taliban. The consensus of the network at a point in time is the mean of all node values. In the absence of exogenous influence, a steady-state consensus will be achieved.

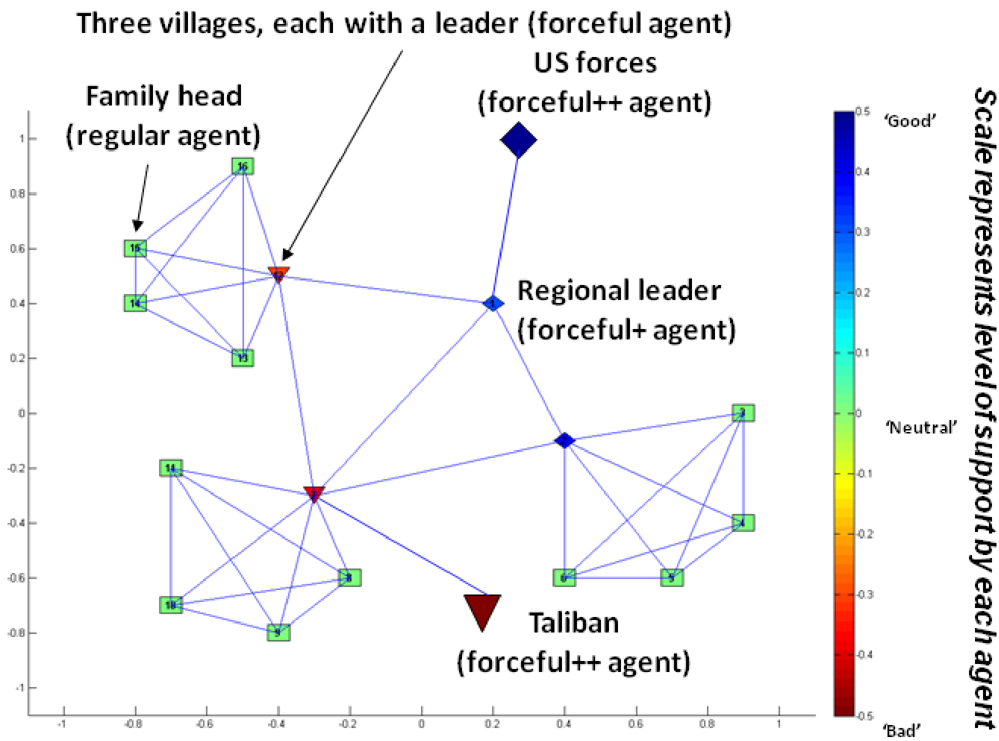


Figure 13. Illustrative network model. The color of each node indicates value, i.e., the measure of the agent's current attitude.

The state of the system is the set of values for the nodes in the network. Changes in the state of the system, i.e., transitions, occur when two nodes interact. The transition resulting from an interaction depends upon the forcefulness of the agents. In the interaction between two agents the possible outcomes are (1) no change in values, (2) one agent's value moves closer to the other's, or (3) both agents' values move closer together. The model treats each of these outcomes as occurring with some probability that depends on the forcefulness of the two agents. In practice, the forcefulness depends on each agent's position in the society and personality factors that may be difficult to observe and quantify. In an exchange between two agents, the agent most likely to

change in value is the less forceful of the two and the amount of change depends on a parameter that measures consistency of attitude. Furthermore, change does not always occur. The three possibilities are: (1) agents i and j reach a pair-wise consensus; (2) agent j exerts influence on agent i, where the parameter ε_i measures the tendency for agent i to resist change to his/her attitude in response to the interaction; and (3) agents i and j do not agree and both retain their original attitudes.

The model has been instantiated in a Monte Carlo simulation, which facilitates investigation of alternative methods for introducing influence. For example, will a particular influence have a greater effect on the overall consensus if it is first introduced to a forceful agent (i.e., someone in a position of authority) or at a lower level in the social hierarchy? The model described above focuses on the steady-state behavior of the network, but new investigations are exploring the dynamic behavior where opposing points of view compete for influence.

3.2. Change Detection

Identifying a shift in the normal pattern of activity or behavior can alert observers to important events. Shifts in the content or sentiment of social media sites could indicate a rise in political discontent, possibly as a prelude to civil unrest. Changes in the pattern of online searches about common medical conditions could suggest an outbreak of disease. Differences in consumer spending after implementation of a new economic policy could indicate the effects of the policy. In all of these cases, however, some level of random fluctuations is expected and normal. The methodological challenge is to detect the changes that are, in some sense, "real." In this section, we briefly examine some methods for detecting changes and illustrate the process with a simple example.

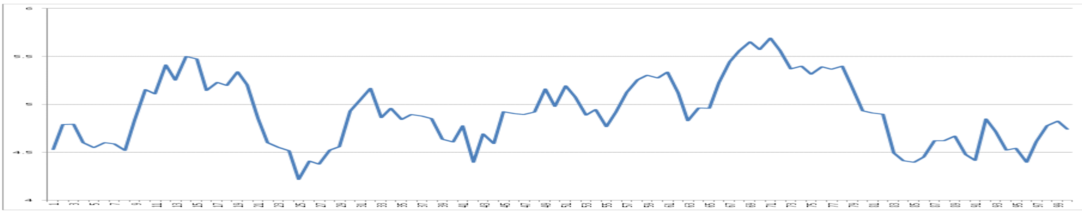
A fundamental difference exists between two types of change detection problems (Irvine, 1982). In one case, we know the time of the possible change and want to know if a shift really did take place. In the second case, we continuously monitor a process or condition and want to detect a change at any point in time. In the above examples, the assessment of the new economic policy is an instance of the first type of change. We know when the new economic policy was implemented and we want to assess its effects. The examples of political unrest and disease outbreak fall into the second type of change detection. The events could occur at any point in time and only continuous monitoring can detect them.

For the first type of change detection, standard statistical methods can address many of the problems that arise in practice. If researchers have access to data both before and after the relevant point in time, they can apply standard techniques to test for a difference between the two time periods. The second type of analysis—detecting the change at an unknown point in time—poses the tricky analytic problem (Basseville & Nikiforov, 1993; Brodsky & Darkhovsky, 1993; Chen & Gupta, 2000). Rather than present the mathematical treatment of this issue, we illustrate the practical implications with an example.

Consider a sequence of observations collected over time. In the spirit of our first example, these observations might show the percentage of posts on a blog that exhibit discontent with the

government. We expect some fluctuations in this percentage as various events occur and news stories are reported. Using synthetic data, we present two scenarios: one with no change and one where a real change occurs (Figure 14). Note the random fluctuations in the two data series.

Example with no change:



Example with change:

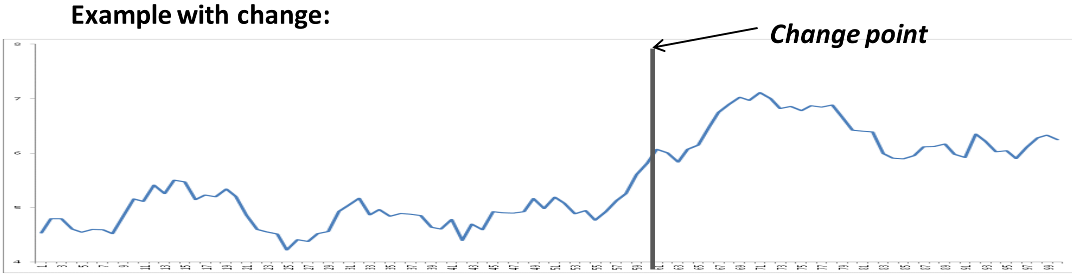


Figure 14. Illustrative time series data with and without changes.

The challenge is to detect the true change without being deceived by the random fluctuations. First, suppose an analyst mistakenly thinks that standard statistical methods can be applied to this type of problem. We present this case because it illustrates the fundamental difference between the two types of change detection problems defined above. A naïve analyst might try to apply a standard statistical technique. Suppose one used the Student's t-statistic to look for a change at each point in the series (Figure 15). This analysis erroneously indicates numerous changes when in fact no change has occurred. These incorrect changes or *false alarms* will mislead all subsequent analysis.

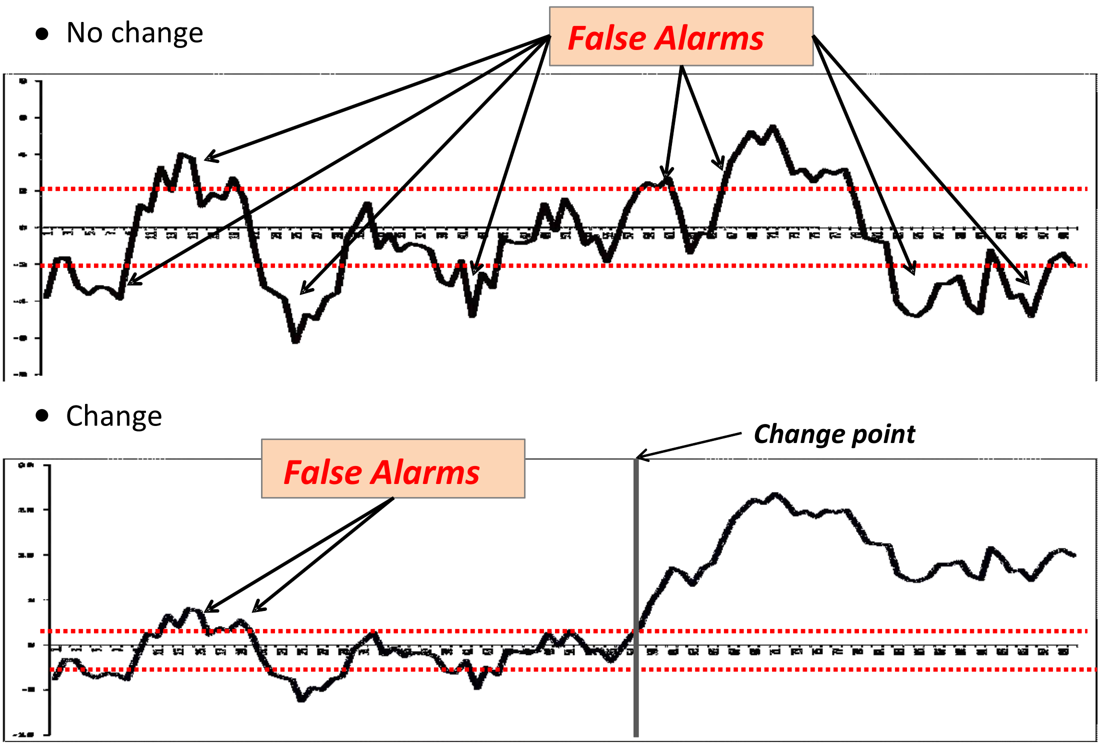
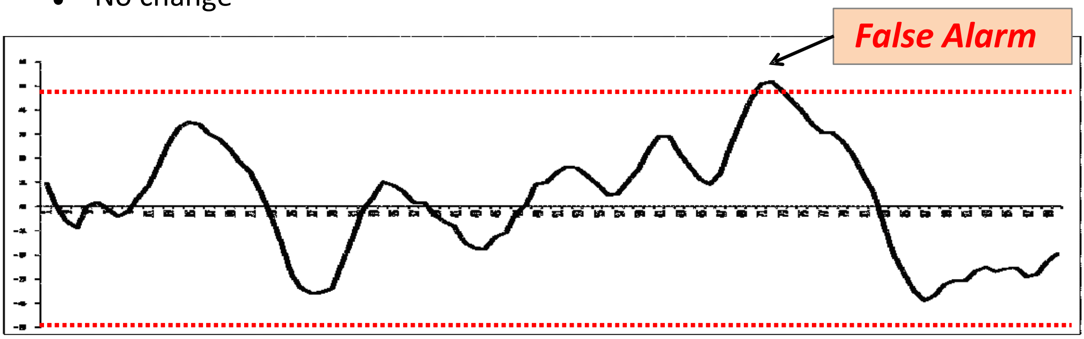


Figure 15. Application of the Student's t-test to detect a change.

Now we repeat the analysis with an appropriate test procedure. Statistical methods to handle the detection of a change at an unknown point in time apply to activities such as quality control for manufacturing, target tracking, and biomedical research. The common element in many of these techniques is that they operate sequentially on the data to detect changes as soon as possible after they occur. Another class of methods has been developed for retrospective or forensic analysis of change points. Searching for a change in the series involves an inherent trade-off between *missed detections* (failure to detect a true change) and *false alarms* (alerting when no change has actually occurred). The statistical procedures have thresholds that can be set according to the acceptable risks for these two types of errors. In our synthetic example, the choice of thresholds led to one false alarm, but accurate detection of the change (Figure 16).

- No change



- Change

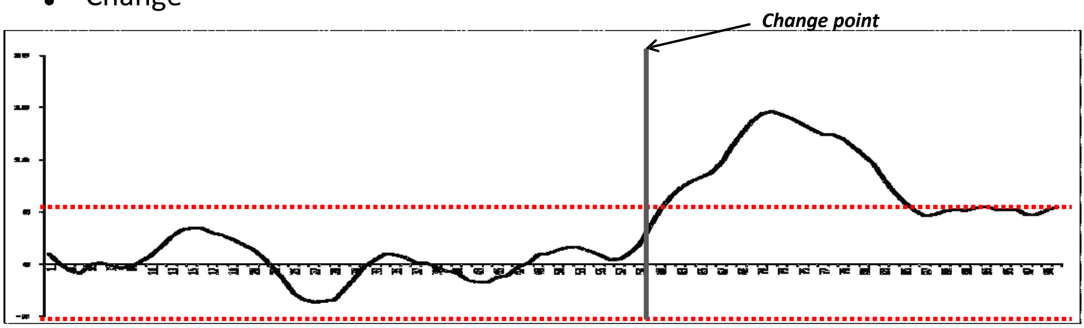


Figure 16. Applying an appropriate test procedure yields far better results.

A related problem affects assessments of social network stability. Changes in the network over time could indicate a response to action by exogenous influences or shifts in behavior for other reasons. Noise in the observation of the network will produce random fluctuations that might look like changes when no true change has occurred. Random fluctuations in the process can mislead techniques that "detect" change by using heuristics or by observing that something is "different" from before. Similarly, as we saw above, naively applying a standard statistical test will lead to incorrect decisions.

Network stability analysis uses statistical methods to detect significant change points in the graph-based representation of the network, while guarding against incorrect use by a naive user. Extending statistical change point methods to graph-based random variables enables a useful approach to network stability analysis. In our simple example, Figure 18 shows metrics computed from estimates of the network over successive time periods. For simplicity, the example shows a series of scalar values, but the appropriate metric could be a vector representing a set of statistics or the actual estimates of the directed graph. Applying a cumulative sum (CUSUM) technique (van Dobben de Bruyn, 1968; Wu, 2005) reveals the correct change point (Figure 17). Additional discussion of CUSUM techniques appears in the text box.

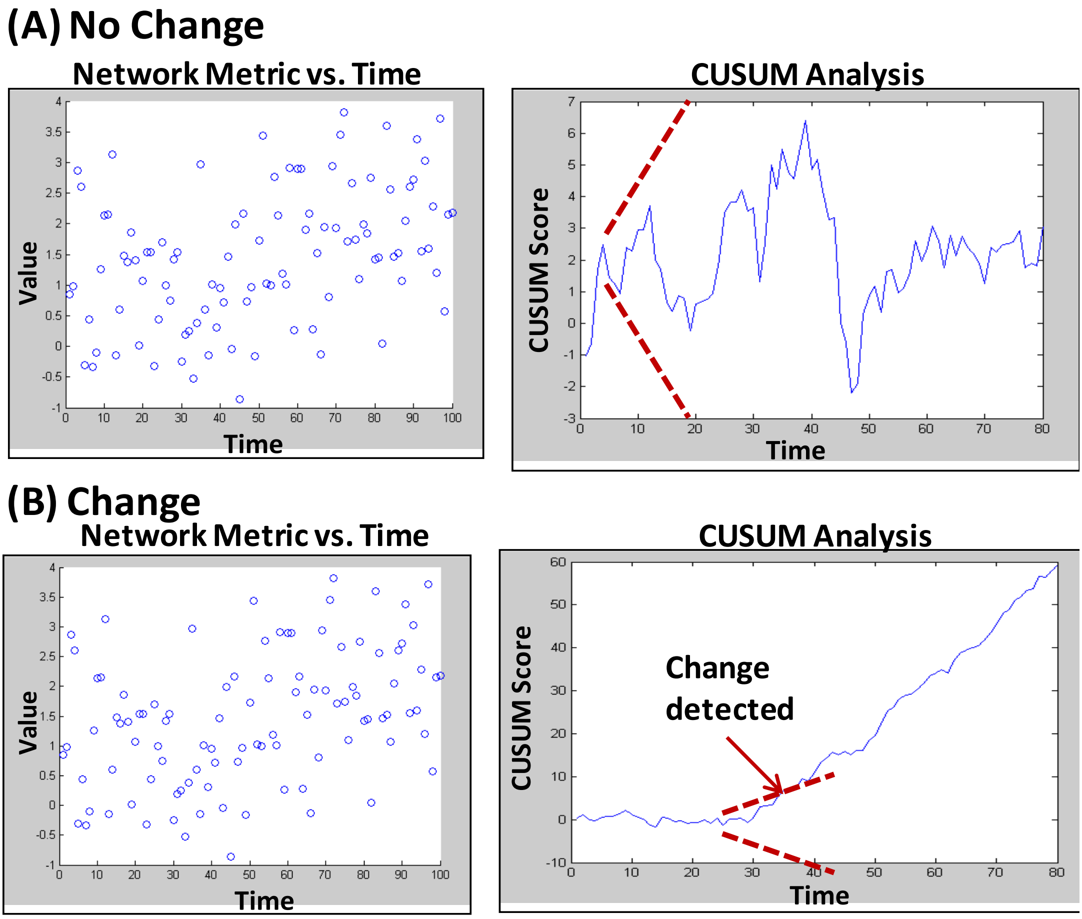


Figure 17. Notional depiction of change detection. Upper plots (a) show a case with no change and lower plots (b) show a significant change. The CUSUM technique correctly indicates when and where significant changes occur.

CUSUM Tests

The CUSUM test is a statistical procedure for detecting a structural change in a model for time series data. The method is a special application of a sequential procedure that has been widely applied in quality control for manufacturing processes and to model economic data. The objective of the technique is to detect a change in an underlying process as early as possible.

CUSUM Tests *continued*

For example, if $\{X(t)\}$ represents the average price of cotton clothing in a particular country, one could model this as a function of various factors that influence prices. The model for θ could depend on labor costs for workers in the garment industry, the price of raw cotton, seasonal factors that influence demand, and possibly other variables.

A change in the model would indicate a shift in the structure of the economic factors that drive the prices.

The motivation for the technique is that the time series can be modeled by

$$X(t) = \theta + \varepsilon(t)$$

where $\{ \varepsilon(t) \}$ represent independent and identically distributed errors with mean zero and finite variance. Often $\varepsilon(t)$ is also assumed to be Gaussian. Under these conditions, $X(t) - \theta$ represents the observed error in the model.

As long as θ is the appropriate model the sum of these deviations has expectation zero and a variance determined by the variance of $\varepsilon(t)$ and the number of observations. In general, the statistic

$$S(T) = \sum_{t=1}^{T} [X(t) - \theta]$$

is a Gaussian process with expectation zero and a variance that grows over time. The CUSUM test compares $S(T)$ to limits defined by the variance and the levels of acceptable type 1 and type 2 error. When the statistic $S(T)$ wanders beyond these limits, we judge that a change has occurred.

4. Technology Gaps

Methods for processing and analysis of many data sources have equipped researchers with new tools for sociocultural investigations. However, many challenges remain. Some of the key gaps in current technology span the full range from data collection to data management and analysis. As newer technologies address these challenges, methods available for processing and analyzing data will become appropriate not just for researchers but also for wide operational use.

4.1. Data Collection

Researchers need better methods for defining data needs and understanding the nature of the data collected. In particular, while social media are emerging as a data source of interest that provide a tremendous amount of information, they raise a serious concern with regard to understanding how findings based on social media might generalize to the broader population. Unlike traditional survey research, we lack good sampling models for exploring social media. Many younger, technology-savvy people have embraced this new form of communication, but we need better understanding of how these people differ from those not using these channels of communication.

A related gap arises in learning how to collect data from traditional sources for new applications. Remote sensing and imagery analysis have been applied successfully to a number of earth science and intelligence needs, but are just emerging as tools for social science research. For researchers to exploit imagery in this new context, the imagery quality, spectral bands, and frequency of collection must be adequate to support the analysis. Traditional methods for specifying imagery collection needs used technical parameters, such as the ground sample distance of the imagery, or functional requirements expressed using the National Imagery Interpretability Rating Scales (NIIRS) (Irvine, 2003; Leachtenaur & Driggers, 2001;). The research community has not yet developed the framework for expressing imagery collection needs for social science applications. The development of the Civil NIIRS (Hothem, 1996) represented a step in this direction, but much work remains.

4.2. Data Management

The volume of data available today is overwhelming. Sociocultural analysis, like other disciplines, will benefit from the revolution in Big Data. In particular, new data storage and management technology will make it possible to perform analyses that were inconceivable a few years ago. New methods for handling data, including data representations, will facilitate the application of new analytic techniques. The emergence of cloud computing offers researchers the potential to run larger scale data analysis, modeling, and simulations that were once impractical.

4.3. Analysis

Extracting information from unstructured data remains a major research challenge. While new methods emerge every day, researchers need efficient and effective ways to represent or model data arising from multiple, heterogeneous sources. How does one combine video analysis with data from Twitter? We need to enhance and mature the mathematical tools that make true multisource analysis practical.

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6 Current trends in the detection of sociocultural signatures: data-driven models[1]

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1. Introduction

Challenges to the security, health, and sustainable growth of our society keep escalating asymmetrically due to the accelerating pace of global change. The increasing velocity and volume of information sharing, social networking, economic forces, and environmental change have expanded the number and frequency of "game-changing moments" that a community can face. Now more than ever, we need anticipatory reasoning technologies based on sociocultural understanding to detect, analyze, and forecast potential change so that we can plan appropriate interventions to neutralize adversaries and protect the public (Costa & Boiney, 2012). The creation of such a "social radar" starts with the detection of sociocultural signatures in data streams.

By harvesting behavioral data and analyzing them through evidence-based reasoning, we can detect sociocultural signatures in their context to support situation awareness and decision making. Developers use the harvested data as training materials from which to infer computational models of sociocultural behaviors or calibrate parameters for such models. Harvested data also serve as evidence input that the models use to generate insights about observed and future behaviors for targets of interest. This input often results from assembling data of diverse types and aggregating them into a form suitable for analysis.

To train or run a model, we must analyze data needed to bring out the categories of content relevant to the domain addressed. If, for example, we are using messages that a group has broadcast to model that group's intent to engage in violent behavior, we must process those messages to extract and measure indicators of violent intent. We can then use the extracted indicators and the associated measurements (e.g., rates or counts of occurrence) to train/calibrate and run computational models that assess the propensity for violence expressed in the source message.

Ubiquitous access to the Internet, mobile telephony, and technologies such as digital photography and digital video have led to the emergence of social media application platforms such as Facebook, YouTube, and Twitter that are altering the nature of human social interaction. The fast and increasing pace of online social interaction introduces new challenges and opportunities for

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gathering sociocultural data. Challenges include the development of harvesting and processing techniques tailored to these new data environments and formats (e.g., Twitter, Facebook), the integration of social media content with traditional media content, and the protection of personal privacy. As modelers address these and other challenges, many new behavioral data and data analysis methods become available that are shaping social computing as a strongly data-driven experimental discipline with an increasing impact on the decision-making processes of groups and individuals alike.

In this chapter, we review current advances and trends in the detection of sociocultural signatures. We present specific embodiments of the issues discussed with respect to the assessment of violent intent and sociopolitical contention. We begin by reviewing current approaches to the detection of sociocultural signatures in these domains. Next, we examine novel methods for harvesting data from social media content. We then describe the application of sociocultural models to social media content, and conclude by commenting on current challenges and future developments.

2. Current Approaches to Sociocultural Signature Detection

This section defines sociocultural signatures and reviews existing methods for detecting them. For expository purposes, we use the modeling of sociopolitical contention and violent intent as the case study, but the methods described apply to other domains as well.

We distinguish between sociocultural data signatures (SDSs) and sociocultural model signatures (SMSs). An SDS can be envisioned as a set of attribute-value pairs describing a data record, as defined in (1), and exemplified in (2) with reference to violent intent (*vi*), where attributes denote classes of words (e.g., *military* = {*war, soldier, weapon…*}) and the associated values indicate how frequently the instances of the attribute occur in a given message.

(1) $SDS\!:\!\{DataRecord = \#_i, a_j = v_j, \dots, a_n = v_n\}, n \geq i, j \geq 0$

(2) $SDS_{vi}\!:\!\{TextID = 6, military = 54, law = 12, religion = 33, protest = 25, urge = 10, \dots\}$

Attributes represent parameters or indicators of the sociocultural phenomenon under analysis. The values associated with these attributes either quantify the presence/absence of the attribute or provide a qualitative specification. Quantitative values can be expressed numerically in various ways, including counts as shown in (2), percentages, weights, or Boolean values. Qualitative values provide either a type or token characterization of their attributes. Type values are usually defined as categories within a conceptual scheme such as an ontology (e.g., the concept “positive mood”) that have token values as extensions (e.g., “happy, hopeful, satisfied”). Token values are the real-world entities: for example, the word “happy,” a smiley face, the sound of laughter, or a video sequence of someone smiling. Values can be assigned to attributes manually using the judgment of subject matter experts, or automatically using data mining techniques to find and measure instances of attributes in datasets.

An SMS is a function that takes a set of SDSs as input and then detects and assesses the behavioral pattern supported by the SDS set, as shown in (3) and exemplified in (4). A more complex example

of an SMS is the decision tree shown in Figure 5, which uses SDSs extracted from messages by violent and non-violent groups (e.g., those shown in Figure 4) as training materials to detect messages from terrorist groups and their characteristics.

(3) $SMS\colon \{SDS_i\}_{i=1}^{n} \xrightarrow{yields} Behavioral\ Pattern\ Assessment$

(4) $SMS_{vi}\colon \{\text{MILITARY} >= 36.5, \text{VIOLENT\_ACT} \geq 3.5\} \xrightarrow{yields} p(\text{terrorist\_message}) = 25.22\%$

While it is in principle possible to create data and model signatures that contain all social and cultural factors known to be relevant to human behavior, in practice the size and generic nature of such signatures would make them too cumbersome to generate, maintain, and apply. Therefore, modelers customarily select as specific a focus as needed to address the domain of interest. Even signatures that address a specific behavioral trait, such as the propensity to commit acts of violence, exhibit differences in behavioral indicators and their relative import according to the specific domain of application, e.g., workplace violence (White & Meloy, 2007), terrorism (Monahan, in press; Sanfilippo, McGrath, & Bell, 2013; Sanfilippo, McGrath, & Whitney, 2011), mass murder, insider threats (Greitzer, Kangas, Noonan, Dalton, & Hohimer, 2012), spousal homicide, and public figure stalking/assassination (Meloy, Hoffman, Guldimann, & James, 2012; Meloy, Sheridan, & Hoffman, 2008;).

2.1. Acquisition of SDSs

Content analysis is perhaps the most widely used technique to distill SDSs from data that include surveys, interviews, ethnographies, social media, news wires, and public speeches. This methodology interprets text through categorical annotation to study the content of communication (Holsti, 1969; Krippendorff, 2004). For example, assessing violent intent through content analysis involves identifying categories of meaning correlated with the expression of violent behavior or the lack thereof. Analysts then draw inferences from the occurrence of such categories in the document(s) reviewed to estimate the likelihood that the communication source would engage in violent behavior.

Traditional content analysis, where content categories are defined as sets of words based on explicit rules of coding, relies on manual annotation. Smith, Suefeld, Conway, & Winter (2008), Winter (2011), Suedfeld & Brcic (2011), and Conway, Gornick, Houck, Hands Towgood, & Conway (2011) provide examples of content analysis studies based on manual annotation. Others (Borum, Bartel, & Forth, 2006) use structured professional judgment to generate assessments based on subject matter experts' answers to questionnaires. For example, the Violent Extremist Risk Assessment instrument (VERA; Pressman, 2009) determines the risk that an individual would engage in terrorism, either as part of a group or as a "lone wolf," in terms of ideological, religious, and political motivations, using guided expert judgment based on responses to a previously set list of attributes, as shown in Figure 1.

VIOLENT EXTREMISM RISK ASSESSMENT									
Subject: ______________________________ D. O. B.: _________________ Date:______________									
Administrator: __________________________ Signature: __________________									
Item I.D.	**Items**	**Low**	**Medium**	**High**	**Item I.D.**	**Items**	**Low**	**Medium**	**High**
A.	**ATTITUDE ITEMS**				**H.**	**HISTORICAL ITEMS**			
A.1	Attachment to ideology justifying violence				H.1	Early exposure to violence in home			
A.2	Perception of injustice and grievances				H.2	Family/friends involvement in violent action			
A.3	Identification of target of injustice				H.3	Prior criminal violence			
A.4	Dehumanization of identified target				H.4	State-sponsored military, paramilitary training			
A.5	Internalized martyrdom to die for cause				H.5	Travel for non-state sponsored training/ fighting			
A.6	Rejection of society and values /Alienation				H.6	Glorification of violent action			
A.7	Hate frustration, persecution				*TOTAL*	*HISTORICAL FACTORS*			
A.8	Need for group bonding and belonging				**P.**	**PROTECTIVE ITEMS**			
A.9	Identity problems				P.1	Shift in ideology			
A.10	Empathy for those outside own group				P.2	Rejection of violence to obtain goals			
TOTAL	*ATTITUDE FACTORS*				P.3	Change of vision of enemy			
C.	**CONTEXTUAL ITEMS**				P.4	Constructive political involvement			
C.1	User of extremist websites				P.5	Significant other/community support			
C.2	Community support for violent action				*TOTAL*	*PROTECTIVE FACTORS*			
C.3	Direct contact with violent extremists				**D.**	**DEMOGRAPHIC ITEMS**			
C.4	Anger at political decisions, actions of country				D.1	Sex (Male = High Female = Low)			
TOTAL	*CONTEXTUAL FACTORS*				D.2	Married (> 1 year = High; ≥ 1 year = Low)			
					D.3	Age(> 30 = High; ≥ 30 = Low)			
					VERA	**FINAL JUDGMENT**			

Figure 1. VERA Coding Response Form. Adapted with permission from Pressman (2009).

The increased ubiquity and reliability of text mining techniques has led to progressive automation of the annotation task. Text mining is the process of discovering information in large text collections and automatically identifying interesting patterns and relationships in textual data. This relatively new and highly interdisciplinary research area, which has recently caught the interest of many in the research and industry communities (mainly due to the ever-increasing amount of information available on the web and elsewhere), brings together research insights from the fields of data mining, natural language processing, machine learning, and information retrieval. Text mining is related to data mining—an older research area focused on extracting significant information from data records—but has proven more difficult because the source data consist of unstructured collections of documents rather than structured databases. Many applications now utilize text mining, including question-answering applications, automatic construction of databases on job postings, and dictionary construction. Feldman & Sanger (2007) provide a thorough survey of research in the area of text mining and the ensuing language analysis capabilities.

Linguistic analyses of affective content facilitated by text mining may reveal emotion, mood, behavior, attitude, cognitive state, physical state, hedonic signal, and sensations. In addition, cultural artifacts extracted from such media may point to useful demographic indicators that have potential utility for the detection of sociocultural and psychosocial signatures (Ortony, 2003). Such signatures can vary considerably in complexity. For example, Pennebaker (2011) uses the occurrence of function words to characterize texts authored by terrorist groups as compared to

non-terrorist radical groups. Texts from terrorist communication sources contain a statistically significant higher number of personal pronouns, while texts from non-terrorist communication sources contain a statistically significant higher number of articles. Function words can also be grouped into higher order variables, such as the variable *status*, which measures the presence of "we-words and you-words" and absence of "I-words."

Other methods for extracting sociocultural and psychosocial signatures using text mining techniques are based on specific theoretical approaches to social and political analysis, such as Leadership Traits Analysis (LTA; Hermann, 2003), operational code analysis (Walker, 1990), and social movement theory (McAdam, McCarthy, & Zald, 1996; McAdam, Tarrow, & Tilly, 2001). Trait leadership is defined as integrated patterns of individual behavioral characteristics that identify the effectiveness of leadership styles across a variety of group and organizational situations (Hermann, 2003; Zaccaro, Kemp, & Bader, 2004). Hermann and Sakiev (2011) evaluate leadership styles along seven dimensions—control, power, conceptual complexity, self-confidence, task orientation, distrust of others, and in-group bias – to detect terrorist rhetoric. They identified these seven traits in public statements from political leaders and measured them using the LTA program embedded in the Profiler Plus software (Social Science Automation, 2013; Young, 2001).

Operational code refers to the values, world views, and response repertoire that an individual acquires and shares with other members of an organization. Walker (2011) examines the violent propensities of groups and leaders in terms of their overall political philosophies and their views on how best to achieve them. This examination is based on automated content analysis that used the Verbs In Context System (VICS) to retrieve and analyze the operational codes of leaders and groups from their public statements. As implemented in the Profiler Plus software (Young, 2001), VICS identifies the use of various forms of power attributed to the self and others in a speaker's rhetoric. The system conceptualizes the exercise of power in terms of classes of events (i.e., reward, promise, appeal/support, oppose/resist, threaten, punish). Walker's findings indicate that terrorists have a deterministic view of the political universe; they also believe they exert greater historical control over world events, are less accepting of risk, and are more prone to choose conflict over cooperation than non-terrorist groups.

Social movement theory (McAdam et al., 1996, 2001) explains the emergence of sociopolitical violence in terms of mobilizing structures, political opportunities, and cultural framing (della Porta, 2008; McAdam et al., 1996; Wiktorowicz, 2003;). The analysis of cultural framing unveils the communicative and mental processes that explain how social movement entrepreneurs endeavor to influence their target audiences, and how the target audiences respond. Sanfilippo et al. (2011) combine insights from cultural framing and theories that explain the emergence of violence in terms of moral disengagement, the violation of sacred values, and social isolation in order to detect violent intent. For instance, communicative strategies that involve feelings of moral disengagement such as hate and disgust and focus on religion and military topics tend to be more highly correlated with texts from terrorist sources.

2.2. SMS Development and Evaluation

Modelers have used diverse techniques to develop SMSs. Some models are primarily developed manually, using insights from social science theories. Developers can instantiate these models with evidence from SDSs to provide operational assessments as outlined in (3) and (4). This evidence can be gathered either manually (e.g., through subject matter expert judgments) or automatically through data mining and content analysis (see section 2.1). Other models are derived from SDSs using machine learning methods; as discussed in section 2.1., these signatures are distilled from raw data through content analysis processes that embody insights from social science theories.

2.2.1. Manually developed models

Chaturvedi et al. (2005) present an agent-based model of insurgency in Indonesia based on the analysis and simulation of dynamic interrelationships among grievances, level of resources, and organizational capacity to mobilize members toward insurgency. The model draws on insights from resource mobilization theory (McAdam, Tarrow, & Tilly, 2001; McCarthy & Zald, 2001); see Figure 2. Equations that regulate inputs and outcomes express dynamic relationships among relevant factors. For example, equations define an agent's intention to rebel (I) as a function of grievance (G) and risk propensity (RP): $I = f(G, RP)$. This approach requires the modelers to calibrate agents with evidence relevant to resource mobilization theory (e.g., resources, organization, political opportunities, discontent, and contention). This evidence is mined from open source repositories such as Polity IV, the Indonesia Public Opinion Survey 2005, the CIA World Fact Book, Worldpress.org, and Europa Magazine.

One of the advantages of this modeling approach is that it overcomes the difficulty of understanding situations (e.g., insurgency in Indonesia) for which few comparable and generalizable historical cases exist. For example, researchers might detect insurgency patterns in Indonesia through simulation in a virtual world, where agents interact according to behavioral patterns derived from social science theories (e.g., resource mobilization theory) and informed by evidence mined from open source data.

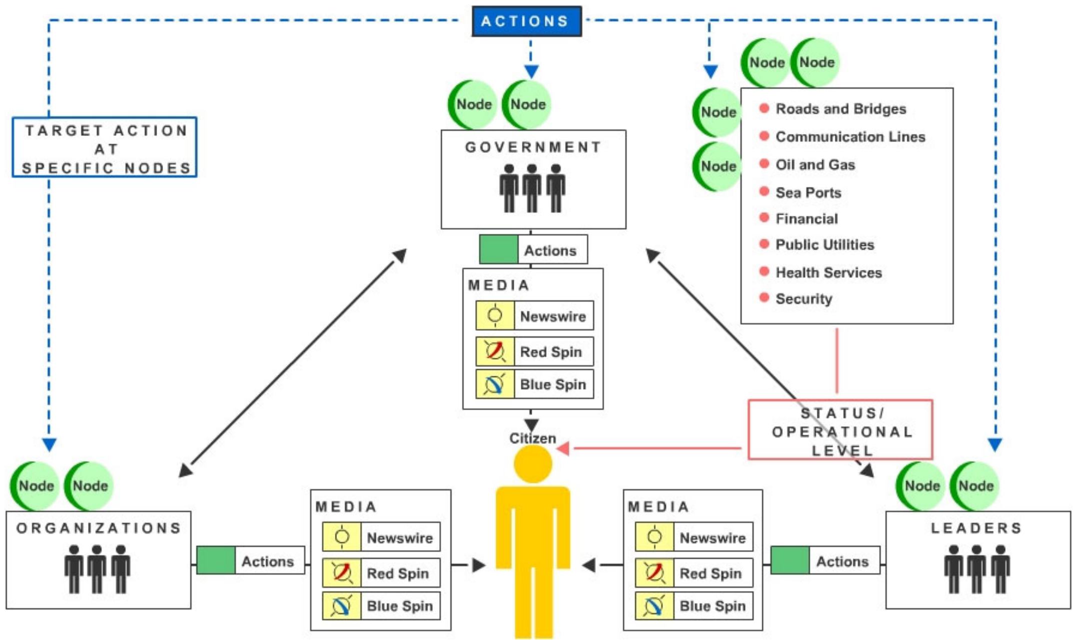

Figure 2. Agent-based model of insurgency. Adapted with permission from Chaturvedi et al. (2005).

Sticha, Buede, & Rees (2005) describe an application of Bayesian nets that enables analysts to perform anticipatory reasoning about a subject's decision-making process by using personality factors derived from LTA (Hermann, 2003) and the Neuroticism-Extroversion-Openness (NEO) Inventory (Costa & McCrae, 1985) as indicators (Figure 3). The relationships among indicators are expressed as probabilities that indicate whether and the extent to which an indicator may cause value changes in other indicators. The application calibrates these relationships by aggregating subject matter judgments. Further, it instantiates indicators with evidence drawn from (a) running the NEO test on input forms compiled by subject matter experts, and (b) processing first-person verbalizations (e.g., speeches and interviews) with Profiler+ (Young, 2001) to obtain leadership personality profiles.

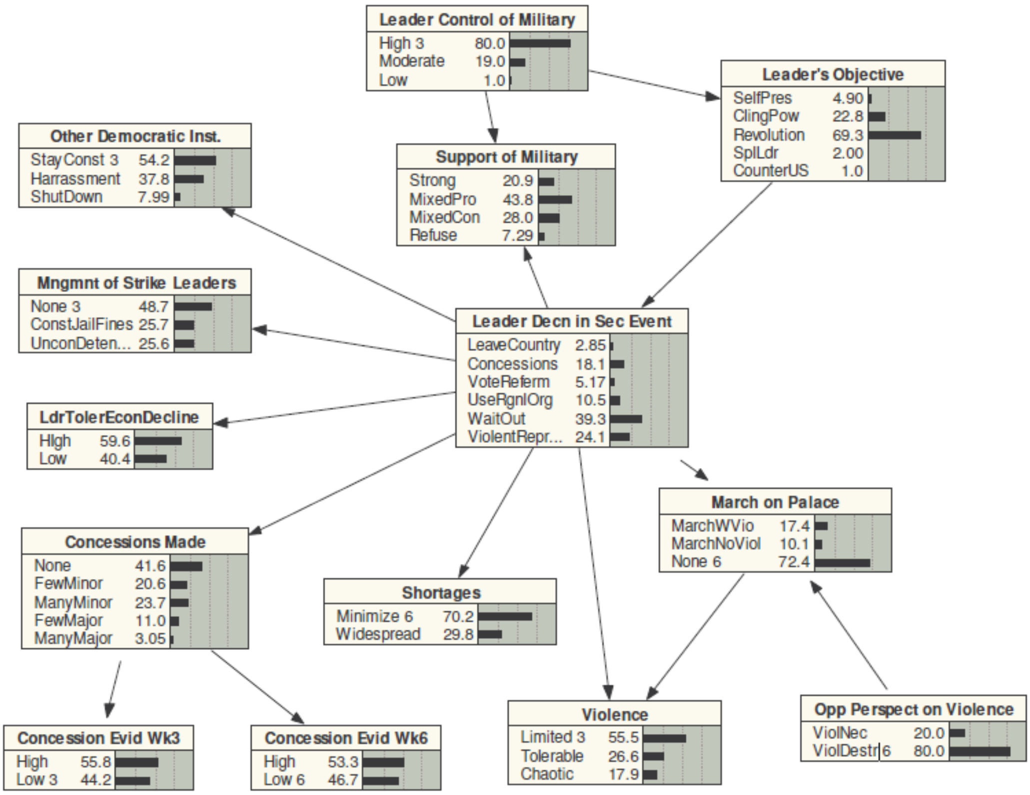

Figure 3. Bayesian net model of a leader's decision-making process. Adapted with permission from Sticha et al. (2005).

The agent-based model discussed by Sticha et al. (2005) is developed through expert judgment and guided by insights from social science theory. However, in this case the modelers use specific processes to extract evidence from relevant data sources (e.g., NEO test and Profiler+). This approach is particularly useful when the relationships among indicators cannot be deterministically established and are thus best expressed probabilistically, and when specific evidence mining techniques can be applied to inform model indicators.

2.2.2. Models derived from SDSs

In the modeling approaches described in section 2.2.1., developers create models manually and then use evidence from SDSs as input to verify how the models respond to specific circumstances, e.g., use recent communications released by the group to detect the group's propensity to engage in violent behavior. Developers can also use those SDSs to derive the model automatically from available historical data through machine learning methods. In this case, the SDSs embody the insight from social science theory and subject matter expertise, and the model infers the relationships between factors and their outcomes algorithmically from the signatures.

For example, Sanfilippo et al. (2011) describe how the propensity and timeframe for engaging in violent behavior can be modeled using decision trees to analyze communication patterns. They extracted SDSs that describe communication strategies from messages authored by targets of interests using an approach that combines content analysis and text mining. The underlying category scheme blends insights from frame analysis (Benford & Snow, 2000; Entman, 2004; Gamson, 1992; Goffman, 1974), speech act theory (Austin, 1962; Searle, 1969), and theories that explain the emergence of violence with reference to moral disengagement (Bandura, 1999), the violation of sacred values (Tetlock, Kristel, Elson, Green, & Lerner, 2000), and social isolation (Navarro, 2009). This category scheme is enriched with a lexicon, as exemplified in Table 1, to enable automated document annotation using text mining methods (Sanfilippo, 2007). This yields SDSs where each analyzed record (e.g., a document) is encoded as an array of values for the selected behavioral indicators, as shown in Figure 4. Model developers can assess the validity of the category scheme as a data annotation device through experiments on inter-annotator agreement in which a set of human annotators use the category scheme to mark the same data. The resulting markings are then compared to measure the level of agreement, using measures such as the kappa score (Sanfilippo et al., 2007).

Using supervised machine learning techniques with SDSs extracted from training datasets (Figure 4) as training data, developers then build classification models capable of detecting communications that signal the propensity for violence and providing a categorical breakdown of such an assignment. For example, the alternating decision tree model shown in Figure 5 provides a detection model for terrorist and radical non-terrorist messages in terms of frame-based SDSs (Table 1 and Figure 4).

Doc_ID	ADMIN	ECONOMY	LAW	MILITARY	POLITICS	RELIGION	SECURITY	SOCIOLOGY	ACCEPT	ACCOMPANY	ADMIRE	ADMIT	…
3	0	2	5	5	7	0	0	0	0	0	0	0	…
6	2	2	2	5	1	5	0	3	0	0	1	0	…
9	78	61	29	66	69	36	6	5	4	1	2	0	…
10	36	57	44	99	95	100	9	28	2	2	6	0	…
17	38	53	45	97	77	115	1	17	9	1	10	2	…
…	…	…	…	…	…	…	…	…	…	…	…	…	

Figure 4. SDSs derived from a collection of documents (e.g., speeches, interviews, book chapters, and newswires). Each row below the headers represents a document; each column represents a feature or category used for sociocultural analysis and the values of that feature in each document.

Table 1. *Partial representation of the Frames in Action annotation scheme*

Top Level Categories	**Intermediate Categories**	**Lexical Extensions**
MESSAGE DELIVERY	ILLUSTRATE	*help, aid assist, …*
	TRANSFER MESSAGES	*tell, explain, cite, …*
	INSTRUMENTAL COMMUNICATION	*call, sign, broadcast, …*
QUEST FOR RESONANCE	HELP	*help, aid assist, …*
	DEFEND	*protect, defend, …*
	EQUIP	*reward, arm, …*
	APPROVE	*accept, encourage*
	PAY	*pay, serve, …*
	GIVE	*give, render, …*
	ADMIRE	*support, love, trust, …*
	FREE	*liberate, absolve, …*
CALL TO ARMS	URGE	*pledge, obligate, bind, …*
VIOLENCE & CONTENTION	DISAPPEAR	*die, vanish, …*
	PAIN	*hurt, bother, …*
	POCKET	*imprison, trap, …*
	VIOLENT ACT	*frighten, attack, destroy, …*
	STOP	*end, vanish, kill, …*
	PROTEST	*appeal, reject, argue, …*
SOCIAL ISOLATION	SPATIAL CONFIGURATION	*stand, lie, sit, …*
	LODGE	*stay, reside, dwell*
	WITHDRAW	*retreat, retire, …*
	CONFINE	*commit, confine, …*
	CONCEAL	*hide, isolate, …*
MORAL DISENGAGEMENT	MANNER OF SPEAKING	*cry, scream, shout, …*
	JUDGE	*attack, punish, …*
	CRITICIZE	*denounce, condemn, …*
	MARVEL	*suffer, fear, wonder*
VIOLATION OF SACRED VALUES	MILITARY	*war, army, soldier, …*
	RELIGION	*god, church, mosque, …*

Note: Adapted from Sanfilippo et al. (2011)

In decision-tree classification (Quinlan, 1986), the model identifies members of a class as the result of a sequence of decisions. As shown in Figure 5, a decision tree typically consists of two types of nodes: test nodes and prediction nodes. The test node describes the condition that must be met in order to make a decision—e.g., MILITARY < 36.5—and the prediction node specifies the results of the decision made—e.g., the numerical contribution of the test node “MILITARY < 36.5” to the recognition of the non-terrorist class (2.25%). Several test nodes can occur in a sequence to indicate the number of decisions that must be taken and the order in which these decisions follow one another to reach a prediction outcome, e.g.,

$$[MILITARY\ >=\ 36.5] \rightarrow [VIOLENT\text{\_ACT} \geq\ 3.5] \rightarrow\ p(terrorist\_message) =\ 25.22\%$$

Test Nodes	Prediction Nodes	
	Non-Terrorist Message	Terrorist Message
| (1)MILITARY < 36.5	2.25%	
| | (7)EVENT_REMOVE < 0.5		3.29%
| | | (10)EVENT_MANNER_SPEAKING < 0.5	2.19%	
| | | (10)EVENT_MANNER_SPEAKING >= 0.5		12.06%
| | (7)EVENT_REMOVE >= 0.5	12.82%	
| (1)MILITARY >= 36.5		19.81%
| | (2)EVENT_VIOLENT_ACT < 3.5	17.33%	
| | (2)EVENT_VIOLENT_ACT >= 3.5		25.22%
| (3)ADMINISTRATION < 8.5		3.72%
| | (8)MILITARY < 0.5	14.37%	
| | (8)MILITARY >= 0.5		2.72%
| (3)ADMINISTRATION >= 8.5	7.32%	
| | (6)EVENT_ILLUSTRATE < 0.5	7.36%	
| | (6)EVENT_ILLUSTRATE >= 0.5		15.66%
| (4)MILITARY < 10.5	5.33%	
| | (5)POLITICS < 11.5		3.70%
| | | (9)EVENT_BELIEVE < 0.5		7.65%
| | | (9)EVENT_BELIEVE >= 0.5	8.09%	
| | (5)POLITICS >= 11.5	22.92%	
| (4)MILITARY >= 10.5		6.17%

Figure 5. Alternating decision tree model that can be used to detect communications from terrorist and non-terrorist radical groups. A prediction value indicates the importance of each decision step. For ease of interpretation, prediction values have been normalized as percentages.

To learn a decision tree classifier from a training dataset such as the one exemplified by Figure 4, a model establishes the sequential order of test nodes according to how informative the nodes' attributes are. The model determines the information content of an attribute by its *information gain* with respect to the classification tasks (Quinlan, 1986; Mitchell, 1997). The information gain of an attribute with respect to a class is the reduction in entropy (i.e., uncertainty) of the value for *the class* when we know the value of the attribute. The test nodes with more informative attributes occur earlier in the decision tree. The model creates test nodes using the available attributes until all data in the training dataset have been accounted for. Typically, not all attributes are used because decision tree learners use pruning strategies to reduce the number of nodes. The number of attributes depends on the specific implementation. The alternating decision tree algorithm (Freund & Mason, 1999; Holmes, 2001) uses a machine learning meta-algorithm called *boosting* to minimize the number of nodes without losing accuracy.

Researchers can use the decision tree model shown in Figure 4 to detect messages from terrorist sources and identify communicative frames in terrorist messages. Messages are first mapped into SDSs, such as the one shown in Figure 4, using automated content analysis. The model then processes the emerging data signatures, which describe messaging strategies, to establish which

test nodes match the data signatures and to generate a detection/prediction (e.g., terrorist or non-terrorist message).

Knowledge of the messaging strategies that terrorists use to influence their target audiences helps operational users to design strategies that neutralize the communicative reach of the terrorists. For example, realization that al Qa'ida (AQ) has suddenly begun to focus its propaganda on young Muslims in Pakistan using frames of "sacred values violation" would highlight relevant geodemographic targets and topics that U.S. planners should address to design a strategy that neutralizes AQ's communicative reach.

No matter how ideologically and operationally close two groups may be, they voice their communication strategies differently to suit the mindset of the social and cultural audience they wish to reach. For example, the transnational Islamist militant organization AQ and its subordinate group AQ in the Arabian Peninsula (AQAP) pursue a terrorist agenda based on the same fundamentalist doctrine. However, while AQAP directs its radicalization efforts to a specific cultural milieu (the Arabian Peninsula), AQ's radicalization efforts have a more overarching goal. The model shown in Figure 5 captures shared motivations and intents of AQ and AQAP as compared to radical non-terrorist Islamist organizations, but does not tell us anything specific about AQ or AQAP. U.S. planners therefore need a comparative analysis of the communicative strategies used by AQ and AQAP to design counterterrorist influence strategies informed by cultural differences between the two groups.

Can the sociocultural data and model signature framework used to develop the model shown in Figure 4 be adjusted to address differences between groups that share the same values and attitudes toward employing violence but operate in different cultural realities? Sanfilippo & McGrath (2011) show that the same annotation scheme used for the violent intent detection model described in Sanfilippo et al. (2011) (analogous to the one shown in Figure 5) can be used to construct detection models that focus on how individual terrorist groups communicate with their target audiences. As illustrated in Figure 6, the detection task in this case involves recognizing whether a specific communication effort originates from AQ or AQAP, identifying the framing features that contribute to one outcome or the other, and determining the extent to which they do so. For example, the model reveals a strong correlation between group-member authorship and AQAP messages, and between group-leader authorship and AQ messages. Also, AQAP radicalization propaganda is more likely to target young Muslims, whereas AQ focuses on a wider set of audiences (e.g., the Muslim faithful as a whole or some regional subset, as well as the United States and its allies). AQAP messages emphasize fulfillment, while AQ's messages focus on rejection and assertion.

We can now combine insights about the framing processes germane to each terrorist group with those from the earlier models that tell us about communicative strategies derived from common motivations and intents of terrorists. The ensuing methodology creates a sociocultural analytic framework that captures both general and culture-specific aspects of terrorist rhetoric, and supports the design of strategic influence interventions for terrorism deterrence.

Test Nodes	Prediction Nodes	
	AQAP Messages	AQ Messages
| (1)author = groupLeader		15.22%
| | (2)ADMIN < 6.5	4.94%	
| | | (4)Event_FULFILL < 0.5		5.49%
| | | | (5)POLITICS < 11.5		16.58%
| | | | (5)POLITICS >= 11.5	10.16%	
| | | (4)Event_FULFILL >= 0.5	7.39%	
| | | | (8)Event_ASSERT < 4	7.99%	
| | | | (8)Event_ASSERT >= 4		4.72%
| | (2)ADMIN >= 6.5		21.23%
| | (9)audience = MuslimYouth	4.66%	
| | (9)audience != MuslimYouth		6.81%
| | | (10)Event_KEEP < 1.5		8.28%
| | | (10)Event_KEEP >= 1.5	8.87%	
| (1)author != groupLeader	21.70%	
| | (3)Event_CORRESPOND < 1	16.52%	
| | (3)Event_CORRESPOND >= 1		8.71%
| (6)Event_REJECT < 0.5	4.51%	
| (6)Event_REJECT >= 0.5		9.06%
| (7)author = member	13.27%	
| (7)author != member		3.90%

Figure 6. Alternating decision tree model (Freund & Mason, 1999) that can be used to detect communications from AQAP and AQ on the basis of frame annotations. A prediction value indicates the importance of each decision step. For ease of interpretation, prediction values have been normalized as percentages.

When sufficient and reliable historical data are available, the automated inference of SMSs from data can help complement and enhance human intelligence. Qualities such as the ability to focus on what is perceived to be most important and the capacity to make quick decisions on the basis of insight and intuition make human judgment uniquely effective (Gigerenzer, 2007; Gladwell, 2005) and have great value in analysis and detection. However, the same qualities can also lead to fallacious reasoning when judgment is affected by memory limitations (Miller, 1956), lack of knowledge/expertise (Klein, 1998), biases due to factors such as increased confidence in extreme judgments and highly correlated observables (Kahneman & Tversky, 1973), positive framing (Tversky & Kahneman, 1981), "groupthink" (Jani, 1972; Surowiecki, 2004), and premature commitment to a single expected outcome (Heuer, 1991). Machine learning methods can help to counterbalance these weaknesses in human judgment by providing an unbiased framework which can then be steered by human intelligence.

Decision trees offer a rather explicit and intuitive classification device for interpreting models learned from the data, as opposed to other algorithms such as support vector machines (Vapnik, 1995) that produce equal or sometimes rivaling results, but whose output is more difficult to interpret. Depending on the nature of the data, other machine learning algorithms may offer better solutions, as discussed in the next section.

2.3. SMS Evaluation

Regardless of which technique modelers adopt for the detection of sociocultural signatures, they must evaluate the resulting models to obtain indications of reliability in the sense of accuracy. Model accuracy is typically measured by comparing the model's expectations against historical data. To increase the significance of the tests, the comparison uses a portion of the training data reserved for testing. Precision, recall, and the F-measure—defined in terms of true positives/negatives and false positives/negatives—provide examples of the methods used to evaluate model accuracy. As shown in Figure 7, the terms *true positive/negative* and *false positive/negative* describe whether the model's class assignments for the test data match the classes observed in the corresponding ground truth data. The terms *positive* and *negative* refer to the class predicted/expected by the model (e.g., ± terrorist), and the terms *true* and *false* establish whether the class predicted by the model matches the actual observed class.

	Class observed in the historical data (ground truth)	
Class predicted or expected by the model	**TP** (true positive) Correct result	**FP** (false positive) Incorrect presence of result
	FN (false negative) Missing result	**TN** (true negative) Correct absence of result

Figure 7. True/false positives and negatives.

As shown in (5) and (6), precision decreases as the rate of false positives (e.g., false alarms) increases, and recall decreases as the rate of false negatives (e.g., misses) increases. The F-measure provides a weighted average of precision and recall, as shown in (7).

$$(5)\ \ precision = \frac{TPs}{TPs+FPs}$$

$$(6)\ \ recall = \frac{TPs}{TPs+FNs}$$

$$(7)\ \ F\text{-}measure = 2 * \frac{precision * recall}{precision + recall}$$

Evaluation helps users to understand a model's reliability. For example, the evaluation results of the alternating decision tree model in Figure 6 indicate that communications from AQAP and AQ can be distinguished with high accuracy (Figure 8), both in terms of precision (low occurrence of false positives) and recall (low occurrence of false negatives).

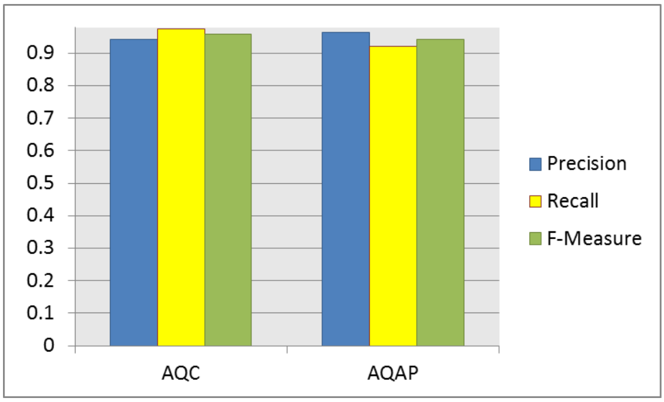

Figure 8. Assessing and comparing model performance using precision and recall measures.

Evaluation also aids users to understand the relative reliability of models derived from the same data but using different algorithms. For example, a comparative evaluation of the alternating decision tree (ADT) classifier shown in Figure 5 with a multinomial Bayesian net (MBN) classifier (McCallum & Nigam, 1998) built by training on the same data (Sanfilippo et al., 2013) shows that the MBN provides higher accuracy (Figure 9). Similar to the tree decision model discussed earlier (Figure 5), the input to a multinomial Bayesian classifier is a document represented as a set of attribute-value pairs indicating the number of times each feature occurs in a document (see Figure 4). To classify a document, the MBN algorithm selects the class that has the highest probability given the feature makeup of the document, as determined by the document-class correlations observed in the training dataset. MBN classifiers are particularly effective when dealing with textual data. They generate output that users can easily interpret in terms of the probability that a term contributes to one class rather than the other, as illustrated in Figure 10 with reference to the violent intent model under discussion.

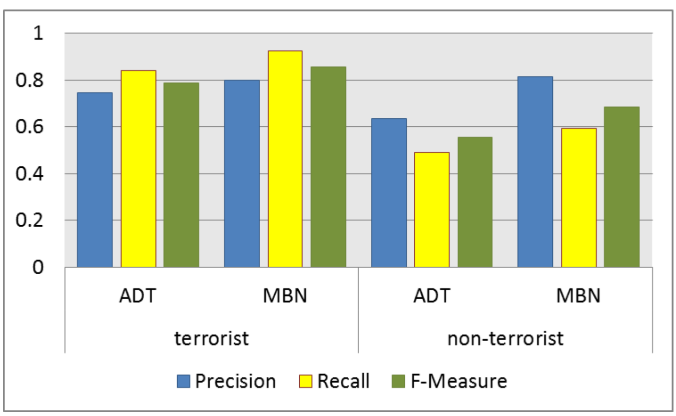

Figure 9. Assessing and comparing model performance using precision and recall measures.

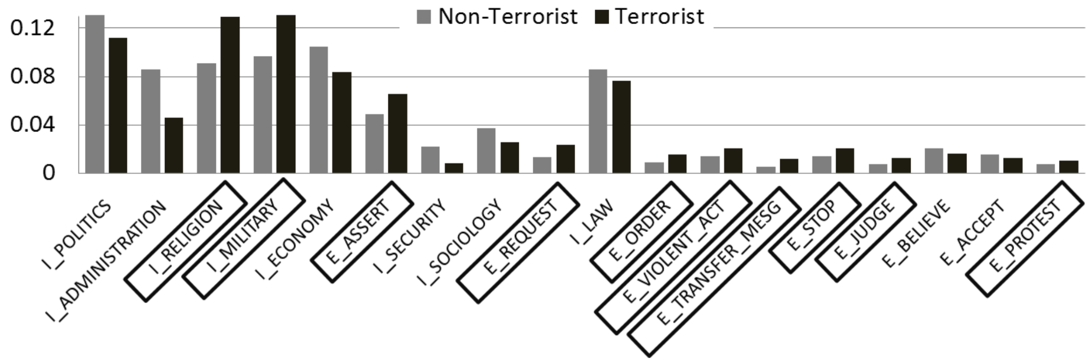

Figure 10. Probabilities relative to the terrorist and non-terrorist classes.

While it is always preferable to use sizeable datasets to train and test models (e.g., datasets with thousands of samples for each class to be detected), this is not always possible, especially when manual annotation is involved. When only a few hundred samples are available for each class to be detected, as in the ADT and MBN models discussed in this section, modelers often use *ten-fold cross validation* to maximize the size of the training dataset. In *n*-fold cross-validation, a randomly selected *n*% of the training data is reserved for testing purposes *n* times; the model then aggregates the resulting *n* evaluation results into a single result using the average function. This enables model developers to use nearly the full dataset for training, but still test the model on a significant number of data examples not used for training.

3. Data Harvesting: Leveraging Social Media

The recent expansion of social media data types and sources has produced a large variety of social media content that researchers can use in addition to more traditional types of data for sociocultural modeling. But before detection, forecasting, or other types of analysis can begin, researchers must obtain, normalize, and manage various forms of data, including social media data.

Social media content serves as a source of real-time, spontaneous data on a wide variety of issues (Sakaki, Okazaki, & Matsuo, 2010). The content varies by type (multimedia vs. text) and by nature (links in a social network vs. a long weblog posting vs. a short tweet of a Uniform Resource Locator [URL]) (Russel, 2011). The data themselves are diverse and unrefined, and are generated in massive quantities (tens of thousands of records per second) and in real time. This real-time quality provides a significant advantage for situation awareness when used appropriately. The unrefined nature of the data offers a fresh perspective on issues also addressed in official sources. Many forms of social media data are produced in streaming environments, but researchers must evaluate them in tandem with batches of traditional, refined data sources, and must do so within the constraints of personal privacy protection guidelines that govern the use and merging of these data and sources.

Most public means of accessing the data place limits on the rate of data that can be harvested, on the fields present in the data harvested, and on the distribution and use of the data. Social media

content appears on a large variety of platforms, each of which comes with its own constraints and policies about obtaining, using, and distributing data. While commercial means of obtaining the data overcome some of these issues, they impose significant costs and technical constraints on the harvesting pipelines. Many of these commercial means are subject to the same constraints as the general public in terms of obtaining data from social media providers. Some of these commercial companies add value by providing a single source for obtaining data (across multiple sources) and translating the data into a common format for reasoning.

As noted, social media data typically vary in format, so modelers must normalize the data into a universal schema for further analysis. This schema must include elements shared by other types of data to enable analysis across data types. Normalization is non-trivial, as differences in language, differences in metadata and data formats (XML [eXtensible Markup Language] vs. JSON [JavaScript Object Notation] vs. HTML [Hypertext Markup Language]), and the time sensitivity of some of the embedded data (e.g., links and shortened URLs) require a robust processing pipeline for transforming, cleaning, normalizing, and validating the harvests. The robustness of any harvesting tool is critical in terms of obtaining complete data. Social media content is often distributed at the moment it is generated. With some systems and providers, retrieving data from a live stream after it has been missed (e.g., because of server downtime, an anomaly in the harvesting software, etc.) is burdensome at best. Other providers simply cannot obtain such data. Yet the lack of these data can alter and bias results in each subsequent stage of sociocultural behavior sensemaking.

A normalization stage typically follows the harvesting of raw social media content. Because some providers format part of the data by breaking individual pieces of data into small elements while others present the data as a single, complex element with a different representation, significant challenges may arise in merging various content types into a single representation that will work for all of the desired analysis. Data containing elements not present in every record (e.g., geolocation) present another technical challenge. Any analysis on this type of data must either supply the incomplete information through approximation/reasoning or must ignore this aspect.

Once social media data become available for analysis, researchers must address other issues before they can use the data. Social media sources inherently raise privacy concerns (Zheleva & Getoor, 2009). Storing and sharing of this type of content present legal concerns, typically arising from the “terms of use” policy for individual sites by which users must abide. Even when sites allow data to be redistributed or shared, they commonly require that the redistributed data be appropriately modified to adhere to any changes made by the original author. Aside from some of the better known issues such as identity theft, sexual predation, and employment screening, continuous concerns arise regarding the quantity of personal information most users share when taking part in various social media services (Gross & Acquisti, 2005). The terms of use agreements established by the data providers often govern subsequent results from sociocultural signature detection and forecasting. This can become quite complicated quickly, as each provider has a separate and often unique policy covering the handling, redistribution, and reasoning that can be done on their data. Unlike many traditional data sources owned by various parts of the government or a small number of well-known and longstanding providers, social media content providers can be as volatile as they are diverse and numerous.

Modern advances in data harvesting technologies enable researchers to gather traditional and social media content with a single system, transform the data into a representation that permits reasoning across diverse data types, and perform all of this technical work within the legal bounds of a diverse set of data providers and content types. Effective harvesting enables researchers to use these data to provide validated, consistent, timely, and unique perspectives for behavioral sensemaking by employing the modeling and detection techniques discussed in the next section.

4. Detecting and Forecasting Behavioral Patterns in Social Media Content

Over the past decade, researchers have demonstrated tremendous interest in quantitatively analyzing the rapidly growing phenomenon of social media communications. Application areas include emergency response, marketing, law enforcement analysis and operations, public health tracking, and education campaigns. The foundational work in social networks comes from social science research conducted decades before the existence of electronic social media (Rapoport, 1957; 1963). The quantitative network science community (largely physicists) has developed a range of methods, beginning with the Entity-relationship model of random graphs (Erdős & Rényi, 1960), extended by identification of the properties of small-world (Watts & Strogatz, 1998) and scale-free (Barabási & Albert, 1999) networks, and by a proliferation of empirical and theoretical studies across a range of disciplines.

SMSs can be successfully applied to social media data. For example, Bermingham, Conway, McInerney, O'Hare, & Smeaton (2009) describe an approach based on social network analysis and sentiment analysis for assessing the attitudes of members of a YouTube group with a radicalizing agenda. They examine the topics discussed by the group members and the sentiment polarity associated with these topics, as shown in Figure 11. They then use the notion of network centrality to assess the relative importance of network members.

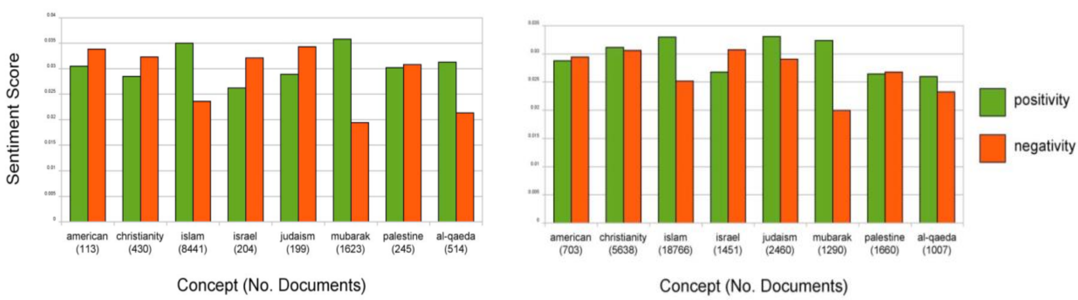

Figure 11. Sentiment analysis results for females (left graph) and males (right graph). Adapted from Bermingham et al. (2009).

Recently, Reynolds et al. (2013) developed several measures to look for signatures of rhetoric used by groups. These measures exploit linkage patterns in networks constructed by filtering billions of tweets based on various term lists (Fortunato, 2010; Newman, 2003; Porter, Onnela, & Mucha,

2009). Their research shows that there is a strong correlation between the use of shared sociolects (e.g. specialized vocabularies) and group structure. More specifically:

- the number of users of multiple terms drops dramatically as the number of terms included in the sociolect grows beyond a given threshold (e.g., six terms)
- association in sociolect-based networks (measured in terms of edge density) tends to be two orders of magnitude stronger than in random term-list networks
- increased term usage is correlated with term dependence in sociolect-based networks, but not in random term-list networks where strong term independence prevails.

Their method explicitly addresses the issue of group sizes, which has proven important in the closely related problem of community detection (Fortunato & Barthélemy, 2007; Lancichinetti & Fortunato, 2011). Ashour (2010) addresses the question of online de-radicalization by leveraging the two growing phenomena of "online radicalization" and "behavioral, ideological, organizational de-radicalization," as a foundation on which to outline a broad strategy for countering the narratives of violent extremists.

Sanfilippo et al. (2013) use automated frame analysis (Sanfilippo et al. 2009; 2011) to map Twitter postings related to the Arab Spring into frame-based feature vectors. They then apply the feature probabilities from the violent intent detection model discussed in section 2.2 (see Figure 10) to capture ebbs and flows in sociopolitical contention across geopolitical regions of interest. The analysis first aggregates Twitter postings by a specific time interval (e.g., days, weeks, months) and then maps each aggregated unit into an SDS. Thereafter, it measures the contention of each data signature as the sum of the probabilities associated with features promoting violent behavior, as shown in (8) where $|F_{ij}|$ is the number of times a feature *i* occurs in message *j,* and $p(F_i)$ is the probability (or weight) with which the feature F_i identifies terrorist rhetoric in the referent model, e.g., the MBN (or decision tree) discussed above.

$$(8)\ \ contention(message_j) = \sum_{i=1}^{n} |F_{ij}| * p(F_i)$$

Figure 12 shows a partial graphic representation of the output of this process for the Twitter postings about Syria.

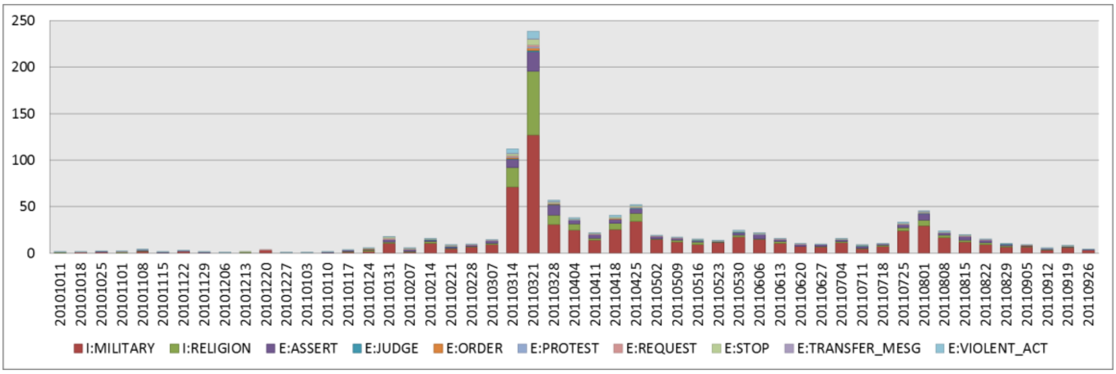

*Figure 12***.** Observed levels of sociopolitical contention in Twitter postings for Syria during the period 01/10/2011 through 09/26/2011. The figure shows only the top 10 attributes from the MBN model described in section 2.2 that have a higher correlation with terrorist messages as compared to non-terrorist messages.

Overall, strong correlations appear between peaks of sociopolitical contention and events that proved decisive in charting the development of the Arab Spring in all four countries for which the researchers harvested and analyzed Twitter data. For example, the strongest spikes in sociopolitical contention for the Syrian data represented in Figure 12 (March 14–21, 2011) coincide with the escalation of the civil conflict in Syria when security forces started to kill protesters. The other Twitter data analyzed showed similar correlations. For example, the highest peaks of contention in the Libyan Twitter data for the period January–September 2011 coincide with the following events:

- *February 2011*: Beginning of protests in Benghazi (2/16/11) and the first casualties among protesters (2/18/2011)
- *March 2011*: First major counterattack by Gaddafi in Zawiyah (3/5/2011), culminating with air attacks on the civilian population that led to Britain and the United States implementing a no-fly zone (3/8/2011)
- *August 2011*: Establishment of the rebel interim government in Tripoli (8/26/11).

This analysis can also be applied to single communication sources by aggregating time series data for individual users.

5. From Detection to Prediction

The development of models to detect sociocultural signatures promotes sensemaking in two major ways. First, it enables situation awareness through an understanding of behavioral patterns that underlie human motivation and intent, as described in the section above. Second, researchers can use the sociocultural signatures that emerge from the detection models to inform prediction models. For example, developers can use the SDSs that result from applying detection models of violent intent to time series data (Figure 12) to train time series models that forecast how sociopolitical contention may grow and highlight the indicators responsible for this growth. With a machine learning approach to time series forecasting (Ahmed, Atiya, El Gayar, & El-Shishiny, 2010),

the same regression algorithms used for building classification models (such as the decision trees discussed in section 2) can help forecast future time series from observed time series, as shown in Figure 13.

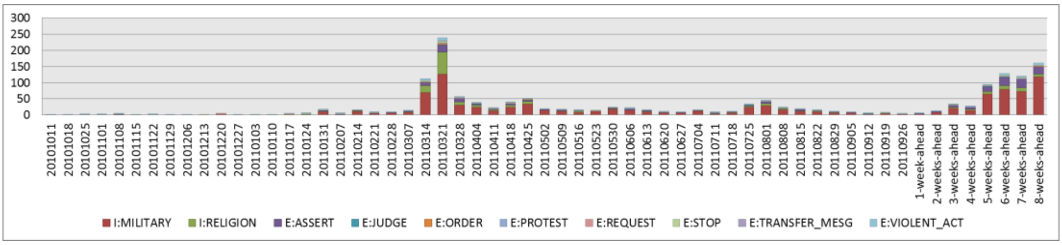

Figure 13. Observed (01/11/2010 through 09/26/2011) and forecast (8 weeks ahead) levels of sociopolitical contention in Twitter postings for Syria. The figure shows only the top 10 attributes from the MBN model described in section 2.2 that have a higher correlation with terrorist messages as compared to non-terrorist messages. This analysis was generated using Weka's time series forecasting capabilities (Weka Time Series).

Forecasted sociocultural signatures can be evaluated using tests such as direction accuracy (DAC). DAC measures the percentage of correct predictions in direction changes by counting the number of times that current and previous values in the observed and predicted time series move in the same direction, as shown in (9). Figure 14 shows the direction accuracy for the eight predicted week steps in the time series shown in Figure 13.

(9) $\frac{1}{n}\sum_{i=1}^{n}\alpha_i$

where: $\alpha_i = 1, if\ sgn(current_i - previous_i) = sgn(current_i^* - previous_i^*)$

$\alpha_i = 0$ otherwise,

and $current_i^*, previous_i^*$ are predicted values.

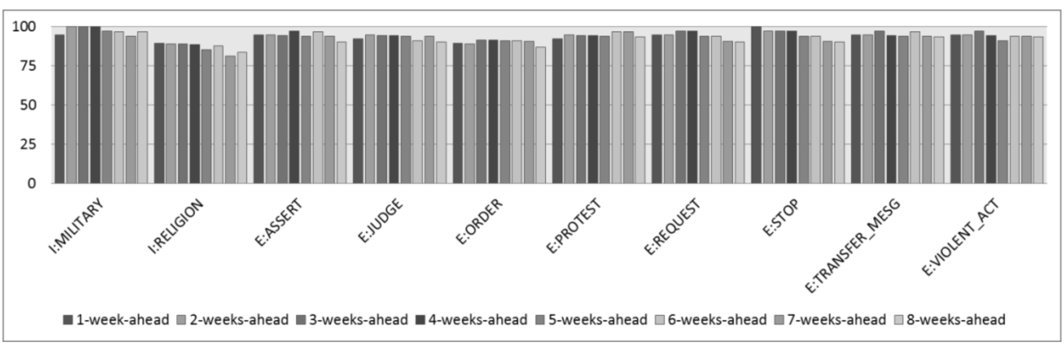

Figure 14. Direction accuracy evaluation for the eight predicted week steps in the time series shown in Figure 13.

The reliability of prediction models such as the time series forecasts described above depends on the quality and amount of the input data, as determined by the signature detection approaches adopted. Modeling techniques that require fewer training data points, such as the application of support vector regression to time series forecasting (Muller, Smola, Ratsch, Scholkopf, Kohlmorgen, & Vapnik, 1997) and smoothing methods to correct modeling inaccuracies due to data sparseness (Zhai & Lafferty, 2001), can partly address these challenges. Ultimately, the availability of better capabilities to harvest social media content and more advanced methods for the detection of sociocultural signatures will determine the ability to develop more reliable prediction models.

6. Conclusions

The extraction of SDSs from document repositories and their use in developing models that detect sociocultural signatures form the basis of sociocultural behavior sensemaking. Applying methods for sociocultural signature detection to social media generates novel and effective intelligence for situation awareness and decision making, and in turn leads to improved sensemaking through the analysis of interactive communication on social media channels. In the next few years we can expect significant advances in understanding and predicting the course of individual and collective behaviors such as sociopolitical contention and the propensity to engage in violent behavior.

Needless to say, the endeavor we have described presents no shortage of challenges and opportunities with regard to technical issues (e.g., harvesting and aggregation, modeling), legal concerns (e.g., privacy protection), and reliability (e.g., provenance-based trust, data sparseness). Data collection and analysis have become both increasingly complex and increasingly rewarding due to the expansion of social media content. Authorship in English—a ripe practice in social media—and manual or automated translation of non-English texts reduce linguistic bottlenecks, but we still lack clear understanding of how the loss of cultural nuances affects data analysis when working with non-native text. The application of computer modeling to communicative processes strongly augments our ability to understand and anticipate human interaction in diverse sociocultural contexts, but the field of content analysis remains too fragmented to provide a comprehensive approach to the study of human communication.

Finally, while computational methods have greatly aided analysis and detection tasks, the combination of human and machine intelligence remains an open issue. The development of collaborative working environments in which analysis and decision making emerge from the concerted articulation of human-to-human, human-to-machine, and machine-to-machine interactions is still in its early stages and only ready for operational use in very limited forms. Successful resolution of these issues or mitigation of the ensuing challenges to reap the associated opportunities will largely determine the success of this emerging analytic endeavor.

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7 Visualization for sociocultural signature detection[1]

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1. Introduction

To discover, distinguish, and locate operationally relevant sociocultural signatures, no tool surpasses the human eye applied to appropriate displays of relevant data. Indeed, the human brain generally outperforms computer-based algorithms at finding patterns in data, particularly patterns that are a priori ill-specified or unknown. For confirmation of this, one need look no further than the captchas[2] used on webpage login screens.

Visualization is the science—and the art—of discovering trends and patterns in data. Those data can be quantitative or qualitative; they can be temporal, spatial, both, or neither. The appropriate visualization of the data allows the viewer to move from the specific to the general, ideally gaining some insight into the larger realm from which the data came, perhaps along with some insight into the underlying social, cultural, or other phenomena of interest. As such, the appropriate visualization is often specific to the particular problem or research question at hand and to the available data.

Done correctly, data visualization can facilitate:

- *Insight*: Data visualization can provide insights, particularly into relationships among variables and trends over time, that may not be apparent otherwise. Appropriate visualizations can make large and/or complicated data easier to understand.
- *Exploration*: Interactive visualization methods permit analysts to assess data from multiple perspectives and contexts; these methods also allow sociocultural experts to bring their expertise to bear on the visualization and ultimate interpretation of the data.
- *Impact*: "Use a picture. It's worth a thousand words."[3] Data visualization is a powerful way to communicate information, relationships, and even the stories present in data.

Data visualization can reveal relationships that summary statistics simply cannot convey. The canonical example is Anscombe's data, plotted in Figure 1 (Anscombe, 1973). Visually these four sets of data clearly show very different relationships between the *x* and *y* variables, yet the means

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[1] Approved for Public Release; Distribution Unlimited. Case Number 14-2487

[2] Captcha is short for *Completely Automated Public Turing Test To Tell Computers and Humans Apart*. See http://www.captcha.net.

[3] Arthur Brisbane, "Speakers Give Sound Advice," *Syracuse Post Standard* (page 18), March 28, 1911.

and standard deviations of each of the *x* variables are exactly the same; the means and standard deviations of the *y* variables are also the same; the correlations between *x* and *y* in each of the four cases are the same; and, even the regression fits are the same. Merely examining some summary statistics without plotting the data could completely mislead a viewer into believing that there is little difference in the underlying phenomena.

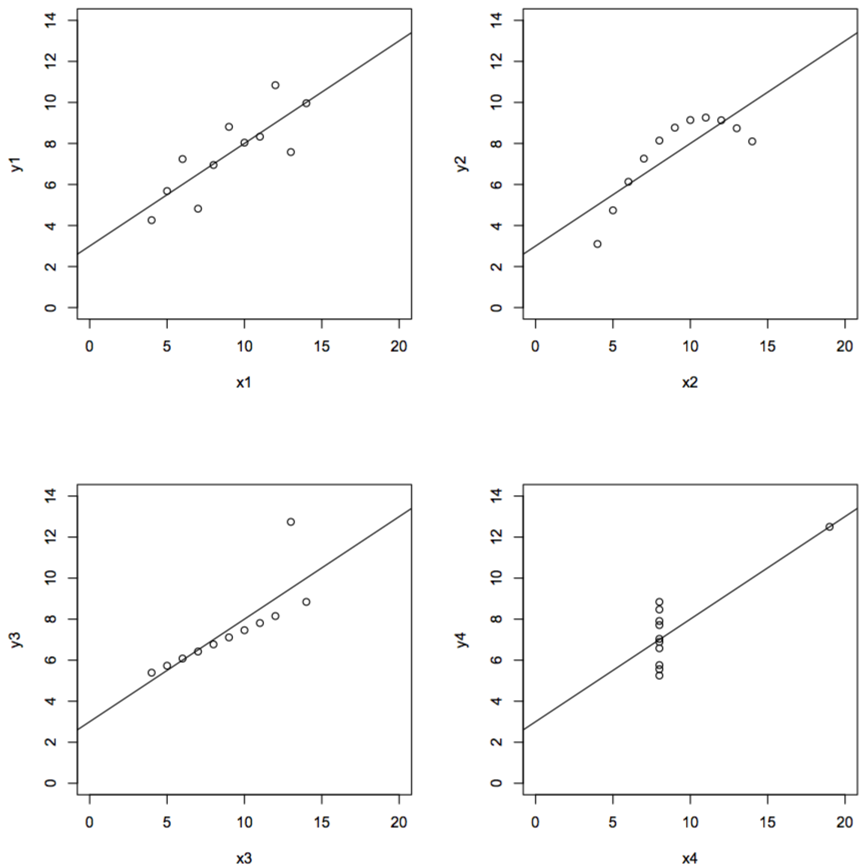

Figure 1. Plots of Anscombe's data, where all the summary statistics match, the regression fits (as shown by the lines) are the same, and yet the relationships between the *x* and *y* variables are clearly different in all four cases.

In terms of communication and collaboration, Sviokla (2009) states that visualization brings the following advantages:

- Great visualizations are efficient—they let people look at vast quantities of data quickly.
- Visualizations can help an analyst or a group achieve more insight into the nature of a problem and discover new understanding.
- A great visualization can help create a shared view of a situation and align folks on needed actions.

As Henry Hubbard said in Brinton's 1939 text, *Graphic Presentation*,

> There is a magic in graphs. The profile of a curve reveals in a flash a whole situation – the life history of an epidemic, a panic, or an era of prosperity. The curve informs the mind, awakens the imagination, convinces (Brinton, 1939, p. 2).

In summary, using visualization has clear benefits, and these benefits increase in direct relation to the size of the data, although even with small data sets such as Anscombe's visualization can provide unique advantages. But unlike Anscombe's data, which is small and simple to visualize via scatterplots, sociocultural data can be large, complicated, and messy. Thus, the real question concerns how one can appropriately visualize such data.

1.1. Visualization for Sociocultural Signature Detection

As defined in the Office of the Secretary of Defense (OSD) Human Social Culture Behavior (HSCB) Modeling program, sociocultural signature detection is one of the four program capabilities: Understand, Detect, Forecast, and Mitigate. The Detect capability consists of "capabilities to discover, distinguish, and locate operationally relevant sociocultural signatures through the collection, processing, and analysis of sociocultural behavior data" (Office of the Secretary of Defense, 2013). The site goes on to say,

> Once the defining features of the sociocultural setting are understood, the next steps are to develop a persistent capability to detect sociocultural behavior signals of interest amidst complexity and noise, and to harvest data for analysis. This entails capabilities for ISR in the area of sociocultural behavior (referred to here as a "social radar"), with particular focus on the challenges associated with open source data collection. It also requires robust systems for storing and managing that data, and tools enabling timely, dynamic analysis.

Visualization, then, supports "enabling timely, dynamic analysis" in terms of both finding relevant signatures and identifying when known signatures change. The former is largely a retrospective exercise in exploring and modeling existing data to identify sociocultural signatures, while the latter is a prospective exercise in monitoring a given signature to identify if and when it changes. Both types of analysis may require a variety of cross-sectional, temporal, and spatiotemporal analytical methods and visualization techniques for infrastructure, social, and other types of network data; Geographic Information System (GIS) and similar types of spatial data; surveys and related types of data; and social media and other types of linguistic data.[4]

Good visualization for sociocultural signature detection must be optimized for the particular application and user. For example, the best methods for visualizing networks may be quite different than those for displaying GIS data. Similarly, GIS methods for displaying point data on maps are not appropriate for displaying areal data from surveys. Some types of social media data

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[4] Visualization is equally important and relevant for the Understand capability. In fact, there is no clear dividing line between the two capabilities in terms of data visualization. Many of the visualization techniques are the same; the main distinction lies in how the methods are employed. See Chapter Three (Understand/Visualization) in this book for additional discussion.

can be effectively displayed as a network, while other types require different visualization methods.

Tufte (1997, 2001, 2006), Cleveland (1993, 1994) and others have addressed the general question of effective design for quantitative visualization. For example, Tufte (2001, p. 13) says,

> Excellence in statistical graphics consists of complex ideas communicated with clarity, precision, and efficiency. Graphical displays should
>
> - show the data
> - induce the viewer to think about the substance rather than about methodology, graphic design, the technology of graphic production, or something else
> - avoid distorting what the data have to say
> - present many numbers in a small space
> - make large data sets coherent
> - encourage the eye to compare different pieces of data
> - reveal the data at several levels of detail, from the broad overview to the fine structure
> - serve a reasonably clear purpose: description, exploration, tabulation, or decoration
> - be closely integrated with the statistical and verbal descriptions of the data set

Of course, the devil is in the details: How can a visualization method meet these criteria for a specific sociocultural analytical method in a given scenario for a particular analyst or researcher?

1.2. Visualization as Part of Data Exploration

Exploratory data analysis or EDA (Tukey, 1977) focuses on summarizing data to make it easy to understand, often through graphics and data displays, and generally without using formal statistical models or hypotheses. As described by the National Institute of Standards and Technology (NIST, 2012):

> Exploratory Data Analysis (EDA) is an approach/philosophy for data analysis that employs a variety of techniques (mostly graphical) to
>
> - maximize insight into a data set;
> - uncover underlying structure;
> - extract important variables;
> - detect outliers and anomalies;
> - test underlying assumptions;
> - develop parsimonious models; and
> - determine optimal factor settings.

NIST goes on to say,

> The particular graphical techniques employed in EDA are often quite simple, consisting of various techniques of:

- Plotting the raw data (such as data traces, histograms, bihistograms, probability plots, lag plots, block plots, and Youden plots).
- Plotting simple statistics such as mean plots, standard deviation plots, box plots, and main effects plots of the raw data.
- Positioning such plots so as to maximize our natural pattern-recognition abilities, such as using multiple plots per page.

Hence, EDA is a methodology for learning from data, often using visualization. The discussion in this chapter emphasizes the visual display of data in support of information exploration for detection of sociocultural signatures. Some may take issue with either an over-reliance on more informal exploratory methods or a failure to use confirmatory methods; however, as Tukey (1977, p. vii) said,

> Once upon a time, [researchers] only explored. Then they learned to confirm exactly–to confirm a few things exactly, each under very specific circumstances. As they emphasized exact confirmation, their techniques inevitably became less flexible. The connection of the most used techniques with past insights has weakened. Anything to which a confirmatory procedure was not explicitly attached was decried as "mere descriptive statistics", no matter how much we have learned from it. ... **Today, exploratory and confirmatory can–and should–proceed side by side.** [Emphasis in the original text.]

Particularly in terms of exploring data to detect sociocultural signatures, EDA is an inherently interactive exercise. As Yi, ah Kang, Stasko, and Jacko (2007, p. 1224) say,

> Interaction is an essential part of Infovis [information visualization], however. Without interaction, an Infovis technique or system becomes a static image or autonomously animated images (e.g., InfoCanvas). While static images clearly have analytic and expressive value, their usefulness becomes more limited as the data set that they represent grows larger with more variables.

1.3. Caution: Apophenia and Pareidolia

Shermer (2008) noted that, "...our brains are belief engines: evolved pattern-recognition machines that connect the dots and create meaning out of the patterns that we think we see in nature. Sometimes A really is connected to B; sometimes it is not." Thus, while the human brain excels at finding true patterns against noisy backgrounds, it also quite capable of over-interpreting pure noise to find nonexistent "patterns." This phenomenon of finding (seemingly) meaningful patterns in random or meaningless data is called *apophenia*; *pareidolia* is visual apophenia (Hoopes, 2011). To anyone who has spent a summer afternoon looking for animal shapes in the clouds,[5] the act of

[5] As Shakespeare (1936) wrote in *Hamlet* : "Hamlet: Do you see yonder cloud that's almost in shape of a camel? Polonius: By the mass, and 'tis like a camel, indeed. Hamlet: Methinks it is like a weasel. Polonius: It is backed like a weasel. Hamlet: Or like a whale? Polonius: Very like a whale."

then believing the shapes represent something other than the coincidental arrangement of water vapor in the upper atmosphere is an example of pareidolia.[6] As Silver (2012, p. 240) says, “Finding patterns is easy in any kind of data-rich environment... The key is in determining whether the patterns represent noise or signal.”

In statistical terms, apophenia and pareidolia are Type I errors: the false positive identification of “patterns” in data. This type of error is non-trivial in sociocultural analyses, particularly since an assumption underlying much of the visualization literature seems to be that a true pattern exists in the data and that the main question is how to best display that pattern. In contrast, exploratory analyses of data in which one looks for patterns that may or may not be present always have the potential for false positives. Under these conditions, it is important to recall the human ability to find fanciful camels in the clouds, and then readily to construct an *a posteriori* rationale explaining the existence and meaning of the camel. But it is equally important to exploit the human facility for pattern recognition, particularly with complex sociocultural signature data. Thus, one challenge with exploratory data visualization and pattern recognition is to balance human and methodological sensitivity for recognizing true patterns against the over-sensitivity that results in false positive “patterns.”

2. Visualization to Detect Sociocultural Signatures

In this section we first review some of the classical methods and approaches for displaying data. We then move on to discuss visualization methods and techniques in the context of fairly general problem and data classes — networks, geographically based data, surveys, linguistic data, and social media — that are particularly relevant to sociocultural signature detection.

2.1. Classical Approaches to Data Visualization

Data visualization has historically been thought of in terms of graphing numerical data. Typically these data were either cross-sectional (i.e., collected at the same point in time) or longitudinal (i.e., collected over time) and were either continuous or discrete, with different methods developed to address each combination. For example, typical graphical methods for continuous cross-sectional data include histograms and box plots, while methods for discrete cross-sectional data include a variety of bar and pie charts, as well as simple tabular summaries. Longitudinal data are most typically plotted on some type of time series plot.

Visualization methods for two variables include scatterplots, mosaic plots, side-by-side box plots, and others. The scatterplot matrix (also known as a pairs plot) permits simultaneous presentation of multiple scatterplots. It is typically displayed in a square showing n continuous variables on both the vertical and horizontal axes, where each row and each column depicts one variable’s comparison with the other $n - 1$ variables. The diagonal is typically left for labels or single-variable graphs such as histograms, since no meaning can be derived from a scatterplot that compares a

[6] A somewhat related phenomenon is the cherry picking of facts to suit a preconceived notion. As Sherlock Holmes warns, “It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to suit facts” (Doyle, 2003, p. 189).

variable to itself. The upper triangle of the square displays the same information as the lower triangle, albeit inverted (i.e., "*X* versus *Y*" translates to "*Y* versus *X*"), so it is not uncommon to display only one side of the diagonal. All benefits of the scatterplot (e.g., visualizing correlation) are inherited, though the scatterplot matrix requires the viewer to cognitively examine and potentially explore each pair of variables individually.

Tukey (1977) and Cleveland (1993; 1994) give a more detailed discussion of classic data visualization methods. These and more recent methods, described in the context of modern statistical software, are discussed in texts such as Wilkinson, Wills, Rope, Norton, and Dubbs (2005), Wickham (2009), Sarkar (2008), and Murrell (2011), although the texts still tend to focus on statistical and quantitative graphics. Discussions of visualization from a media and/or graphical design perspective include Yau (2011; 2013), Steele and Illinsky (2010), and Wong (2010), in addition to the well-known books by Tufte (1986; 1990; 1997; 2006).

Common to most of these methods and most of these discussions is that the data involved are quantitative, typically of low dimension (mainly one or two, though sometimes three dimensions), and the plots are mainly static. Stated another way, the classical data visualization methods are generally not designed for text-based data, photo and video data, high-dimensional data, and geospatial data, all of which are becoming more common at an increasingly greater rate.

Text, photo, and video data are often displayed in small multiples or facets, often called lattice or trellis plots. These are particularly useful for looking at plots of data conditioned on the value of one or more categorical variables. For example, Figure 2 is a lattice plot of the age of patients presenting at a health clinic conditioned on gender (male or female) and ethnicity (unknown, Hispanic, and non-Hispanic). The plot shows clear differences in the age distribution of patients presenting by gender but no difference by ethnicity.

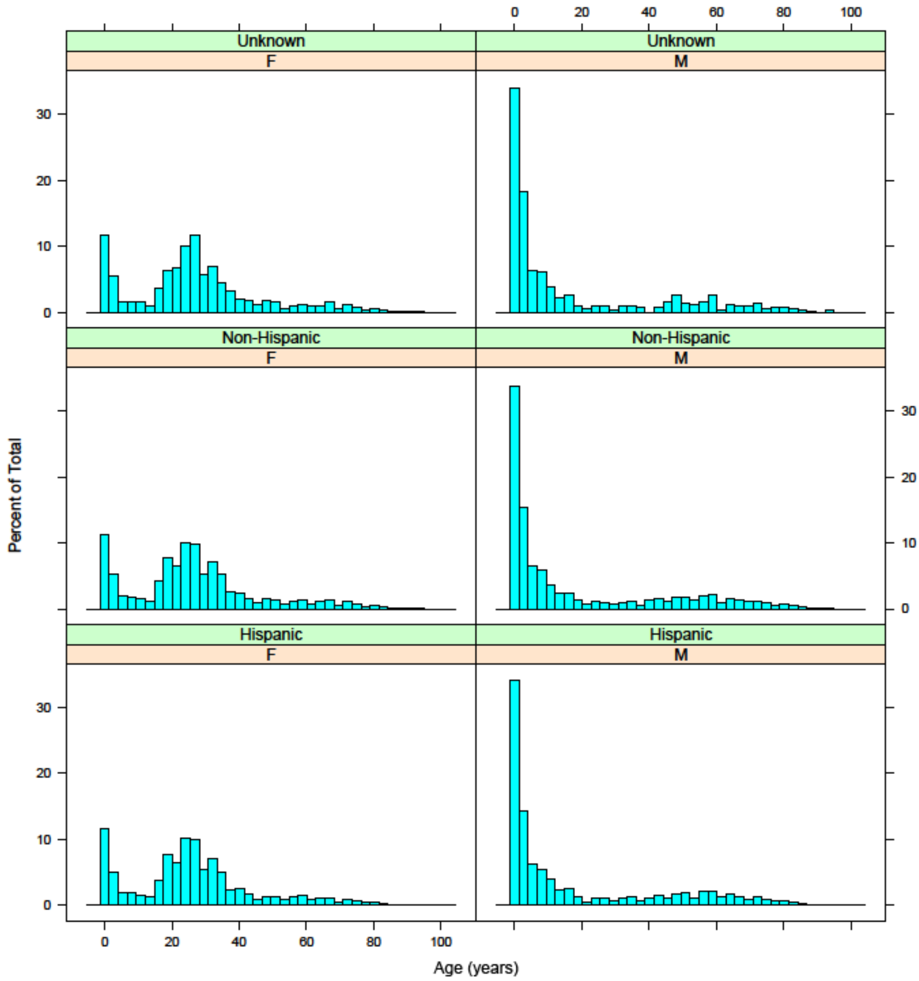

Figure 2. Trellis plot example showing differences in the distribution of health clinic patient age by gender but no difference by ethnicity. Adapted with permission from Fricker (2013).

Rosling (2013) displays multiple variables via bubbles on a scatterplot. In addition to the variables represented on the two axes, the size of the bubble represents a third variable and (optionally) bubble color represents a fourth. His software, *Gapminder World*, provides over 500 variables for comparison; Figure 3 shows an example output. The same data can also be displayed geographically, as in Figure 4, where the two axis variables from Figure 3 (life expectancy and income per person) are exchanged for country centroid latitude and longitude, while the bubble size and color retain their original meanings.

Tufte (2001) cautions against under- or more commonly over-representing the magnitude of the data when using area to display a variable (the mistake is not made in Rosling's work). As Tufte says (2001, p. 57), "The representation of numbers, as physically measured on the surface of the graphic

itself, should be directly proportional to the quantities represented." Tufte proposes a metric called the *Lie Factor*, which is the ratio of the size of the effect shown in the graphic and the size of the effect in the data. Values within 0.95 and 1.05 are preferred, while ratios outside of that range show "substantial distortion, far beyond minor inaccuracies in plotting" (Tufte, 2001, p. 57).

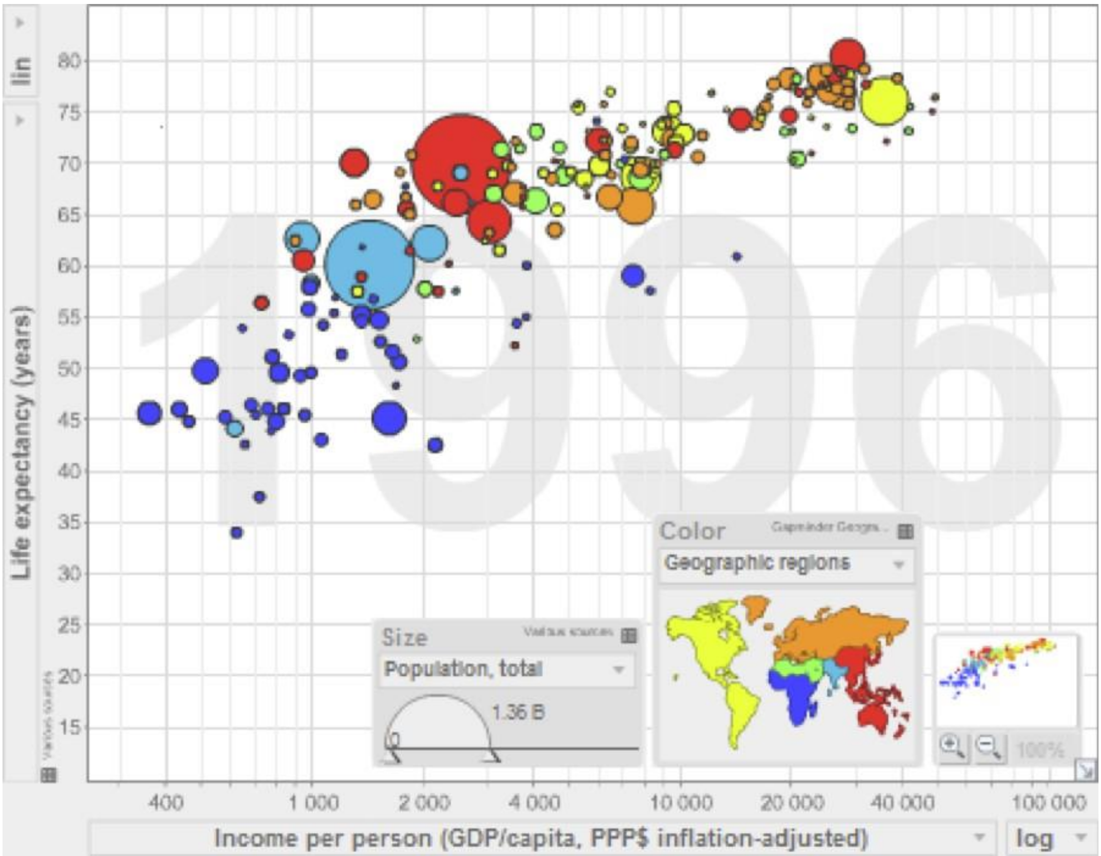

Figure 3. Rosling's *Gapminder World* software provides easy-to-interpret displays of up to four variables, with a fifth presented in a time-series animation. Dimensions are indicated by the two axes plus the bubble size and color. Adapted with permission from *Gapminder World* software display, Rosling (2013).

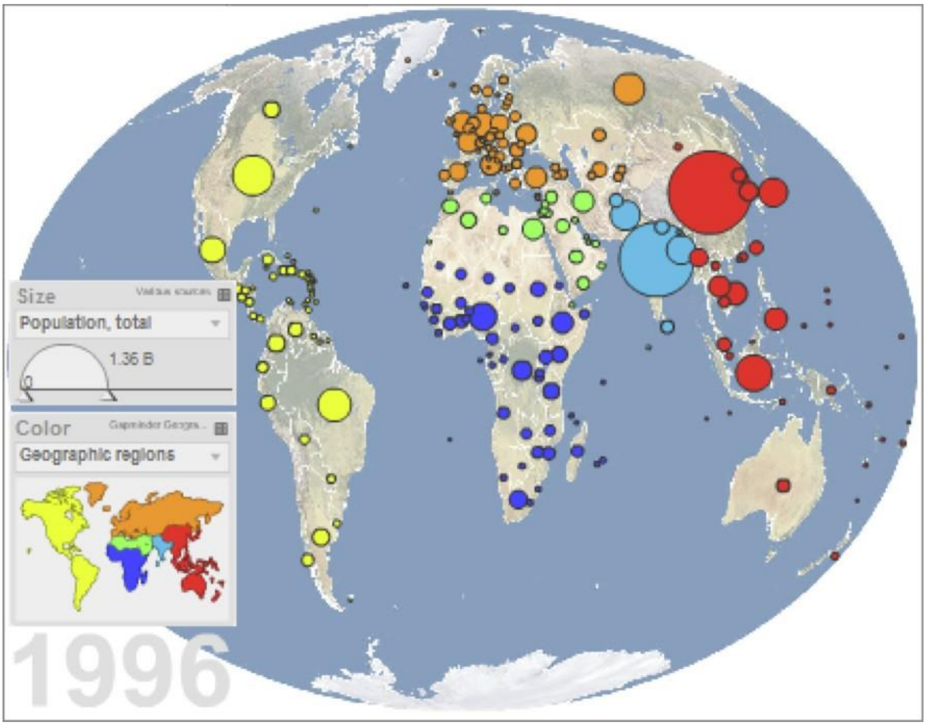

Figure 4. The two axis variables from Figure 3 are exchanged for country centroid latitude and longitude. The bubble size and color retain their relevance. Adapted with permission from *Gapminder World* software display, Rosling (2013).

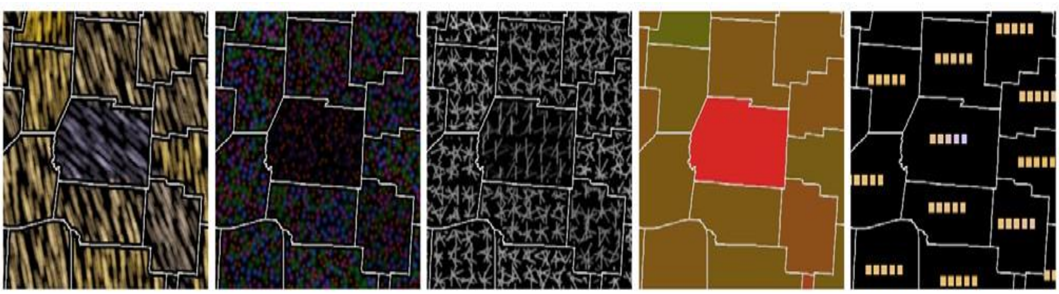

Figure 5. Multivariate visualization techniques evaluated in the study. From left to right: brush strokes, data driven spots, oriented slivers, color blending, and attribute blocks. Adapted with permission from Livingston & Decker (2012).

An individual scatterplot may be enhanced to display one or more additional variables. For example, varying the dot size, color, and/or shape makes it possible to add extra variables to the

graph. LOESS (locally weighted scatterplot smoothing) curves, developed by Cleveland & Devlin (1988), do not add a dimension but may provide insight into the relationship between variables.

Healey, Kocherlakota, Rao, Mehta, and St. Amant (2008) related data display to human perception and automated search strategies, providing a pathway from the data to visual interpretation. They used luminance, hue, size (height), density, orientation, and regularity to a grid to display high-dimensional data. Livingston et al. (2011; 2012; 2013) and Livingston & Decker (2012; 2011) continued their work, intending to display up to ten variables simultaneously on two-dimensional plots. Figure 5 shows five of their techniques.

Perhaps one of the most elegant portrayals of multidimensional data is Charles Minard's flow map of Napoleon's March to Moscow, shown in Figure 6. Tufte (2001, p. 40) credits this graph as displaying "six variables: the size of the army, its location on a two-dimensional surface, direction of the army's movement, and temperature on various dates during the retreat from Moscow. ... It may well be the best statistical graphic ever drawn."

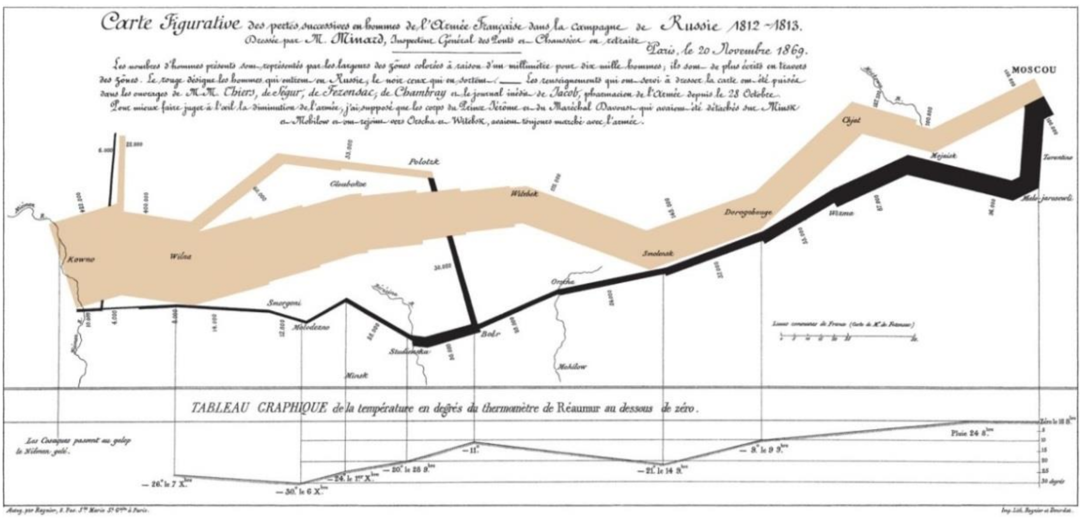

Figure 6. Classic graphic from Charles Minard (1781–1870) showing the progress and fate of Napoleon's army in its march against Moscow. This is a combination of a data map and a time-series, and displays six variables. Adapted with permission from Tufte (2001).

2.2. Network Visualization

Networks occur naturally in many situations. Conceptually they are quite simple, with every entity denoted by a node in the network and linkages between entities denoted by arcs. Visualizing networks in ways useful for learning about and understanding the network, on the other hand, can be anything but simple. For example, particularly with large networks, simply displaying all the arcs and nodes results in the classic "hairball" (see, for example, Figure 7) from which users can discern little about the network. As Krzywinski (2013) says,

> "Hairballs turn complex data into visualizations that are just as complex, or even more so. Hairballs can even seduce us to believe that they carry a high information value. But, just because they look complex does not mean that they can communicate complex information. Hairballs are the junk food of network visualization – they have very low nutritional value, leaving the user hungry."

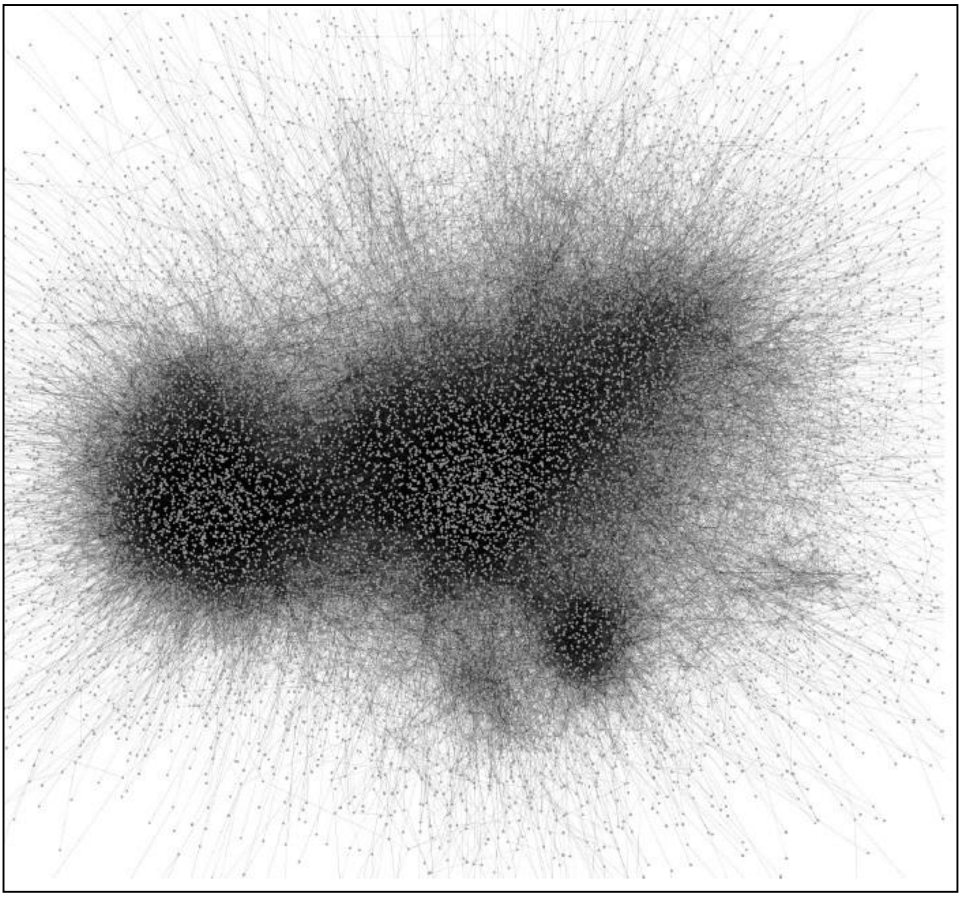

Figure 7. A network visualization of a Facebook friendship network for 15,000 users. A classic "hairball" that provides little insight into the network structure. Adapted with permission from Coscia (2012).

At issue is that "[v]isualizations are useful to leverage the powerful perceptual abilities of humans, but overlapping links and illegible labels of nodes often undermine this approach" (Perer & Shneiderman, 2006, p. 693). As a result, when visualizing networks it is often important either to execute the visualization in interactive software so that the user can explore the network appropriately and/or to subset or highlight the data so that structure is visible. Figure 8 shows an example of the latter approach in which the most connected nodes and associated arcs are highlighted.

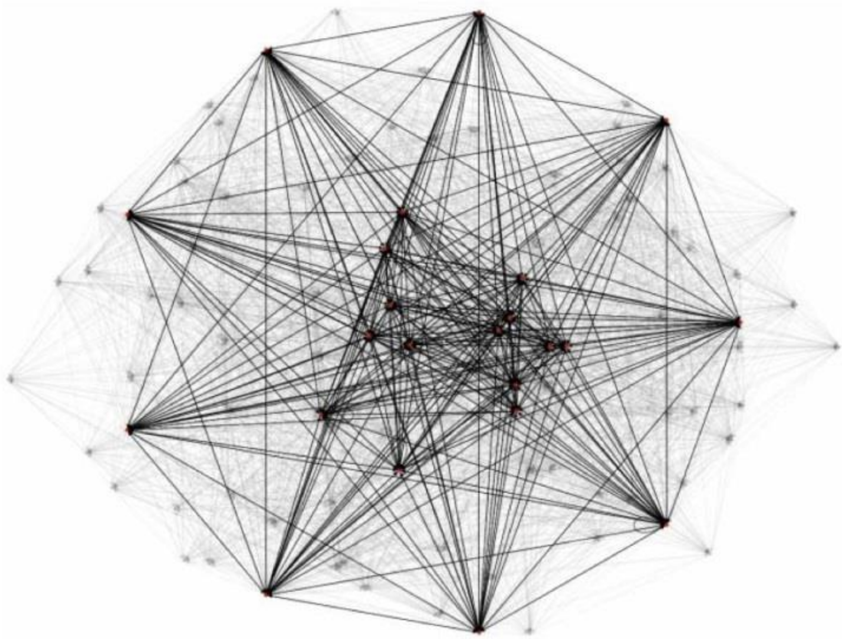

Figure 8. An example of a filtered network that highlights the most connected nodes and their connections to one another. Adapted with permission from Smith et al. (2009).

There are numerous ways to visualize networks. Figure 9 illustrates a few by Krzywinski (2013) using hive plot software. What should be evident is that the most relevant visualization or visualizations is/are tied to the specific problem at hand and the associated data. Furthermore, finding the preferred visualization may require multiple attempts; software that allows interactive exploration and visualization of the network facilitates the search for the best solution.

Interactive network visualization is very much in the spirit of Tukey's exploratory data analysis and in keeping with recommendations by Perer and Shneiderman (2006, p. 40), who promote an "overview first, then details on demand" approach to visualization. Similarly, Viégas and Donath, (2004, p. 1) say, "We posit that basic cartographic principles – such as adaptive zooming and multiple viewing modes – provide system designers with useful visual solutions to the depiction of social networks."

The variety and quantity of network visualization approaches and software are too great to permit a comprehensive review in the limited space available in this chapter. Furthermore, the practice is undergoing rapid development, so any listing will quickly become outdated. Instead, readers should consult on-line resources such as Mobio (2013) for an overview. As an interesting example of self-referential visualization, Figure 10 shows a screenshot of an interactive network visualization of data visualization resources.

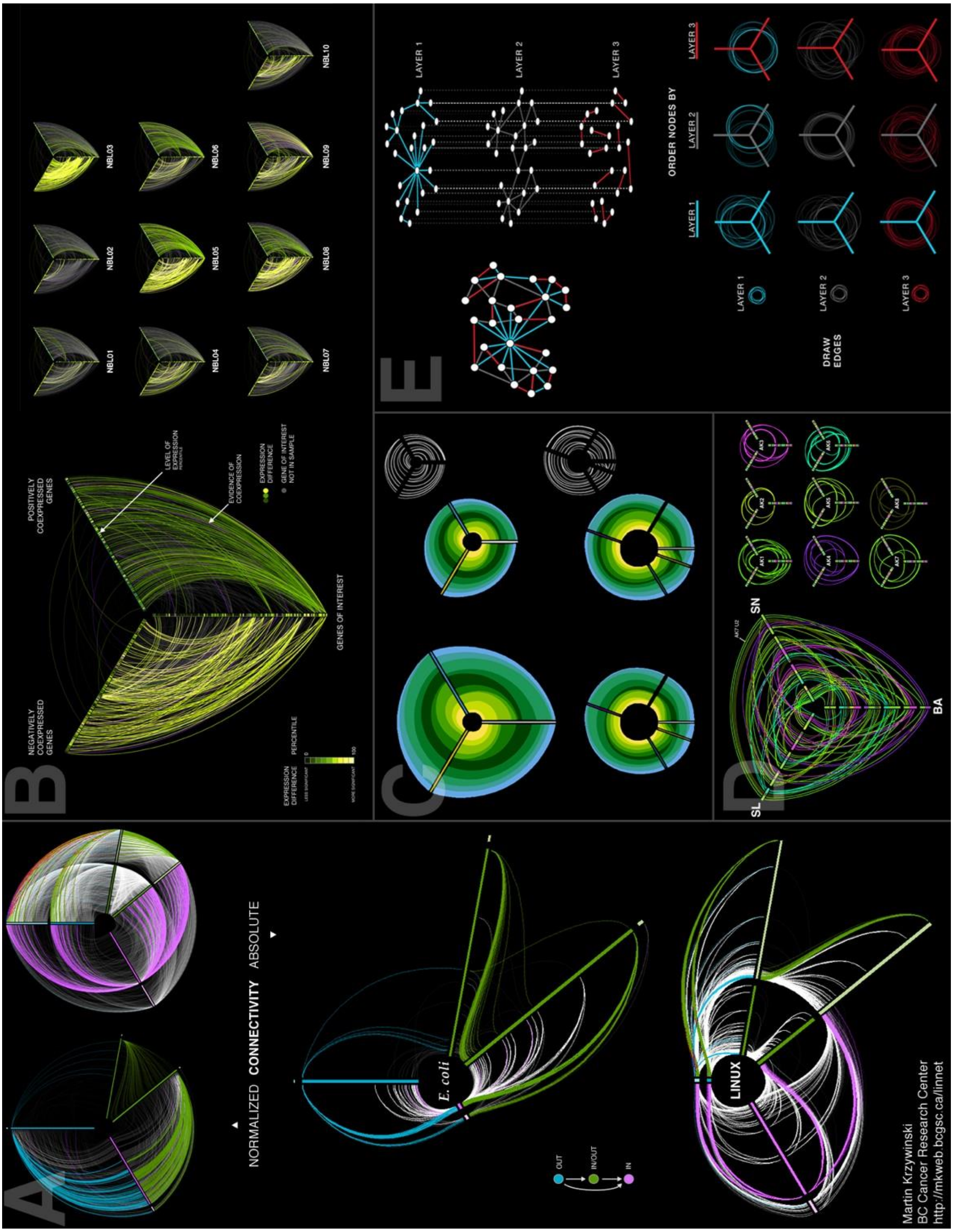

Figure 9. Alternative network visualizations: (a) normalized (top) and absolute (bottom) connectivity; (b) co-regulation networks; (c) network edges shown as ribbons creating circularly composited stacked bar plots (a periodic streamgraph); (d) syntenic network; and (e) layered network correlation matrix. Adapted with permission from Krzywinski (2013).

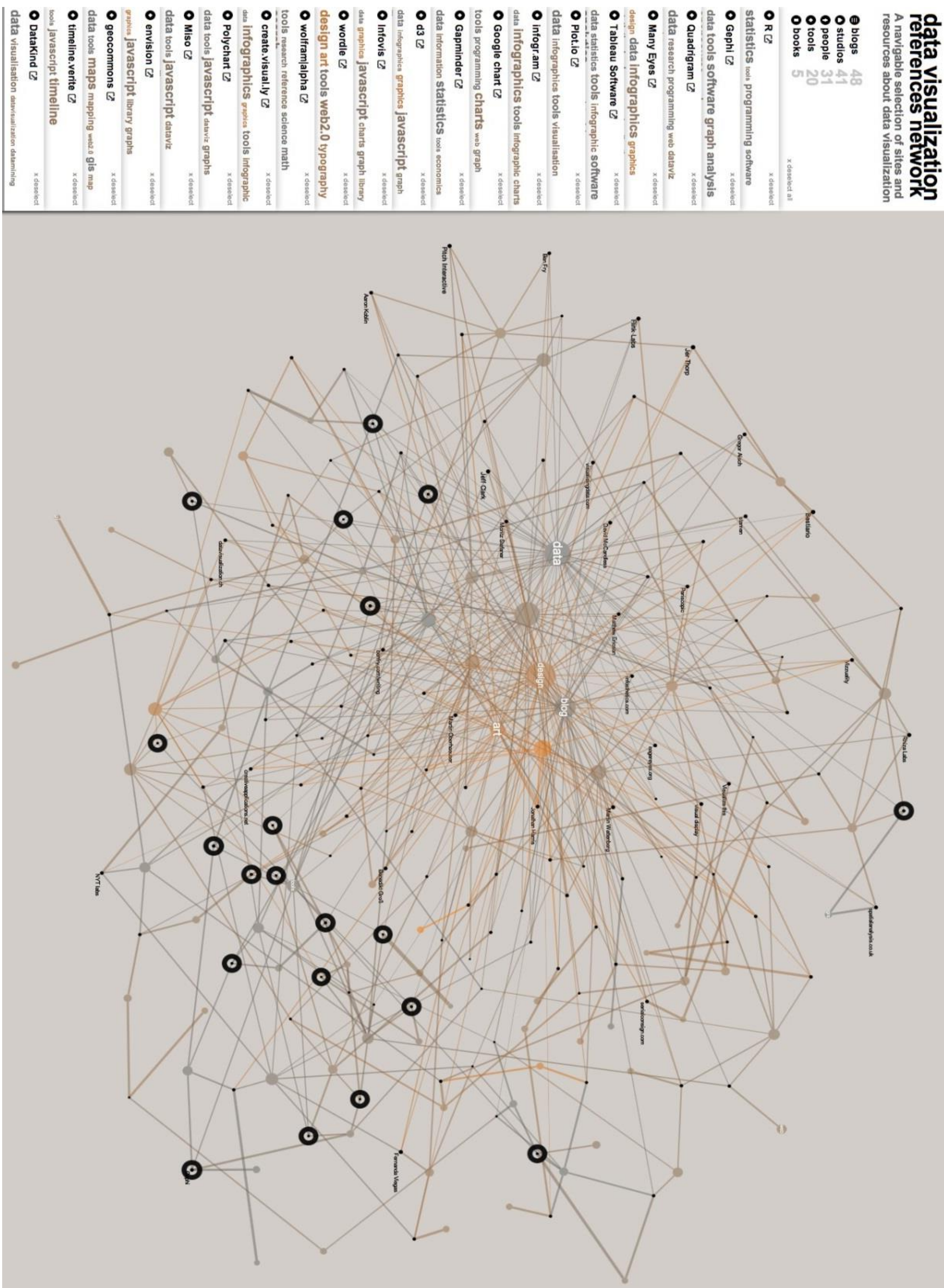

Figure 10. Interactive network visualization of data visualization resources. This particular view highlights visualization software. Adapted with permission from Mobio (2013).

2.3. Visualization of Geographic Information

The visualization of geographic data – the making of maps – has a long history and recent developments in computing have put the display of geographic data within easy reach. Furthermore, the widespread incorporation of Global Positioning System (GPS) capabilities in objects such as mobile phones and freight palettes has produced significant growth in the amount of georeferenced data available to consumers and organizations. Additionally, it is now straightforward to perform analyses, as distinct from visualizations, that would have been much more difficult even ten years ago. By analysis, we refer here to tasks such as identifying the polygons that contain particular points (for example, identifying terrorist incidents with provinces), projecting points onto lines (for example, identifying traffic accidents with road locations), or computing lines of sight (for example, locating regions that cannot be seen from a particular tower). Of course, the distinction between display and analysis is not always sharp.

2.3.1. Coordinate systems

One aspect that sets geographic visualization apart from traditional approaches is that developers must choose the coordinate systems with care. At the start, data are often associated with geographic coordinates—latitude and longitude, typically in degrees. Since the earth is roughly ellipsoidal, geographic coordinates must be associated with a "datum" that characterizes the particular ellipsoidal approximation in use. A latitude, longitude pair for a particular location derived under one datum might be hundreds of meters away from the same pair derived under another datum. A number of datums[7] are available, but the WGS84 datum, used by GPS, is by far the most common. Several computer programs make it possible to convert coordinates based on one datum to another.

Over small areas geographic coordinates can be plotted directly, neglecting the curvature of the earth, but for even moderate distances (say, dozens of miles or scores of kilometers) a projection is necessary. As one interesting example, the two towers of New York's Verrazano-Narrows bridge are 1-5/8 inches farther apart at the top than at the bottom because of the curvature over the bridge's 4,260-foot length.

Dozens of projections are available, with different projections serving different roles. For example, the widely used transverse Mercator projection preserves angles—that is, angles on the map match angles on the ground—and is therefore useful for navigation. The Albers projection shows areas accurately, which might be particularly useful in displaying political data. Figure 11 shows the lower 48 states of the United States under the Mercator (upper) and Albers (lower) projections, together with a grid of lines of constant longitude and of constant latitude. Any text about GIS (for example, Bolstad, 2008) lists and compares the common projections.

Projected coordinates are often displayed as latitudes and longitudes, but sometimes they are converted to UTM, the Universal Transverse Mercator grid system (or perhaps its military analog, the Military Grid Reference System). UTM represents the globe by a set of sixty projections, each six degrees of longitude wide by eight degrees of latitude high. Longitude bands are numbered;

[7] In the geodetic context, the plural of "datum" is always "datums."

latitude bands are lettered. Within a zone, points are labeled with "eastings" and "northings" in meters. This makes it easy to compute lengths and areas directly from the coordinates; within a zone the distortion in a length computed this way is held under 0.1%. Computing distances between points in different zones, however, requires a more difficult computation.

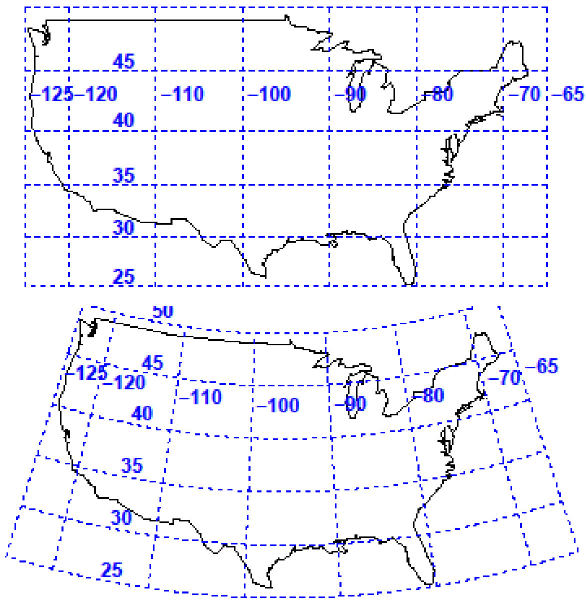

Figure 11. Two projections of the lower 48 states of the U.S.A. The upper shows the familiar Mercator projection, the lower the equal-area Albers projection.

2.3.2. Tools and formats for geographic data

The final product of a visualization is generally a graphic image in digital form. Geographic data can be held, manipulated, and depicted in a large number of formats. Often one piece of software saves the data in projected form, which means that the data may have to be both re-projected and converted to be used in another software system.

Many sets of tools, often known as GIS, are available for displaying geographic data. Among the most popular are the ArcGIS suite from Esri Corporation, which is powerful and comparatively expensive; the free, open-source GRASS [Geographic Resources Analysis Support System] GIS from the Open Source Geospatial Foundation; and the widespread Google Earth, the base version of which is currently offered free by the Google Corporation. This last offers very limited analysis capabilities, but provides a quick way to combine geographic data with pre-supplied aerial photography and road network information.

While different software uses different formats, two widespread formats deserve mention here. ArcGIS stores data in "shapefiles." This is a slight misnomer, since a shapefile is actually a collection

of at least three distinct disc files. While originally intended for ArcGIS, the shapefile format is now openly available and in fairly wide use in other GIS products. Shapefiles generally hold one of four types of displayable data: points (such as locations of specific incidents), lines (such as roads or rivers), polygons (such as the boundaries of states or provinces), and raster data. The first three are collectively known as “vector” data. Raster data appears in grid form; it might be physical, as with a photographic image of the ground, or logical, as in a map showing the availability of fresh water for each cell in a gridded region.

A second format is KML, a text-based format built in XML and supported by Google Earth. KML files can contain both vector and raster data. It should also be noted that the widely used open source statistical environment R can, with the proper libraries, read and write both shapefiles and KML.

The construction of a geographic image generally consists of the superposition of “layers,” each layer consisting of a shapefile or KML file describing some feature of the area being depicted. Because these tools were designed for map-makers, the features are almost always physical, but in principle they might be lines showing connections among individuals, numbers of website hits per square mile, or other non-physical data. As an example of the superimposition of layers, Figure 12 shows three layers used to build a map of Nigeria: a satellite image (top left), state boundaries (top right), terrorist events (bottom left), and then the three superimposed (bottom right). Of course, in making the map the researcher must select not only the layers but their attributes—color, point size, line width, transparency, and so on.

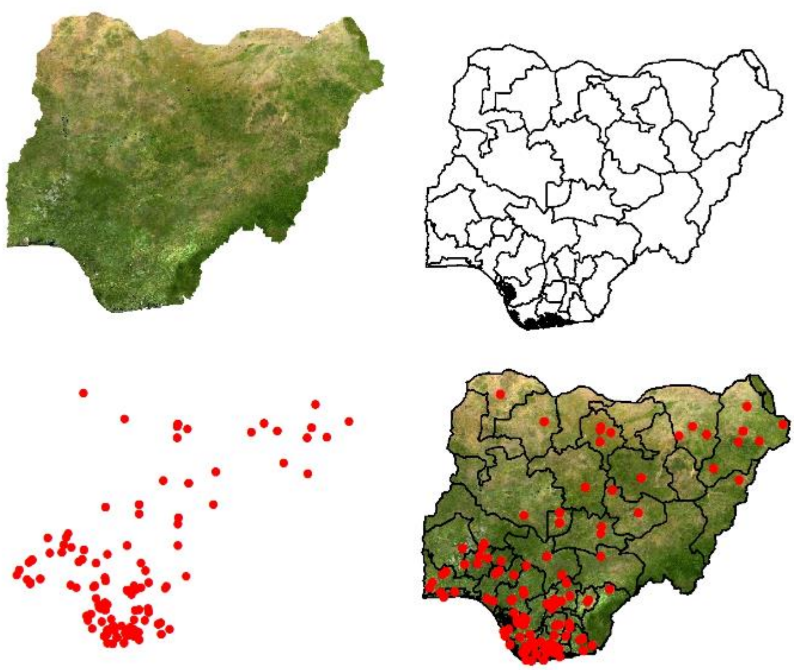

Figure 12. Three layers in a Nigeria map (upper left and right and lower left) and the resulting map in the lower right.

2.3.3. Coloring the map

The researcher's task, then, is to use the correct set of layers to display, and not conceal, the essential information. A map intended to show population density by province would not benefit from the inclusion of railroads or precipitation unless part of the story were that population tends to settle along the railroads, or in areas of higher rainfall.

In the context of human activity, data is often produced in the form of counts by region, say a province. A natural device is to color areas according to the value represented. Such a graph is sometimes called a "chloropleth." However researchers should in general display not counts but count density—that is, counts per area—particularly when areas are quite different.

One interesting technique now available to analysts is that of the "cartogram," in which a map shows regions scaled to represent the quantity displayed, while retaining their respective shapes to the extent possible. Figure 13 shows a map of the 2008 U.S. Presidential election, in which states that awarded their electoral votes to John McCain are red, and those that awarded their votes to Barack Obama are blue in color (Cole, 2012). In this map, the ratio of red area to blue is about 62%, yet the size of the states visually misrepresents that 68% of the electoral votes came from the states that voted for Obama. Cole purposefully included this map as a bad example. In Figure 14, the data and color-coding are the same, but each state is represented by an area proportional to its number of electoral votes (Carter, 2008). This map is about 68% blue. Cartograms can also be drawn with curved boundaries.

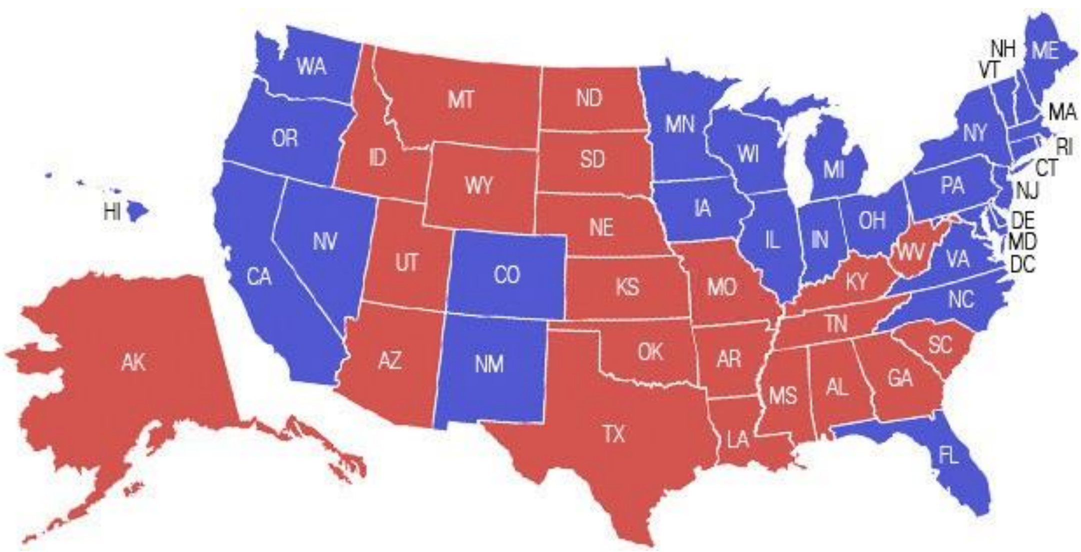

Figure 13. Map showing the states whose electoral votes were awarded to John McCain (red) and to Barack Obama (blue), plus the District of Columbia. About 62% of the map is red, but equal areas do not denote equal densities of electoral votes; Alaska's 570,000 square miles of land are much more visible than Washington, D.C.'s, 68, though the two each contribute three electoral votes. Adapted with permission from Cole (2012).

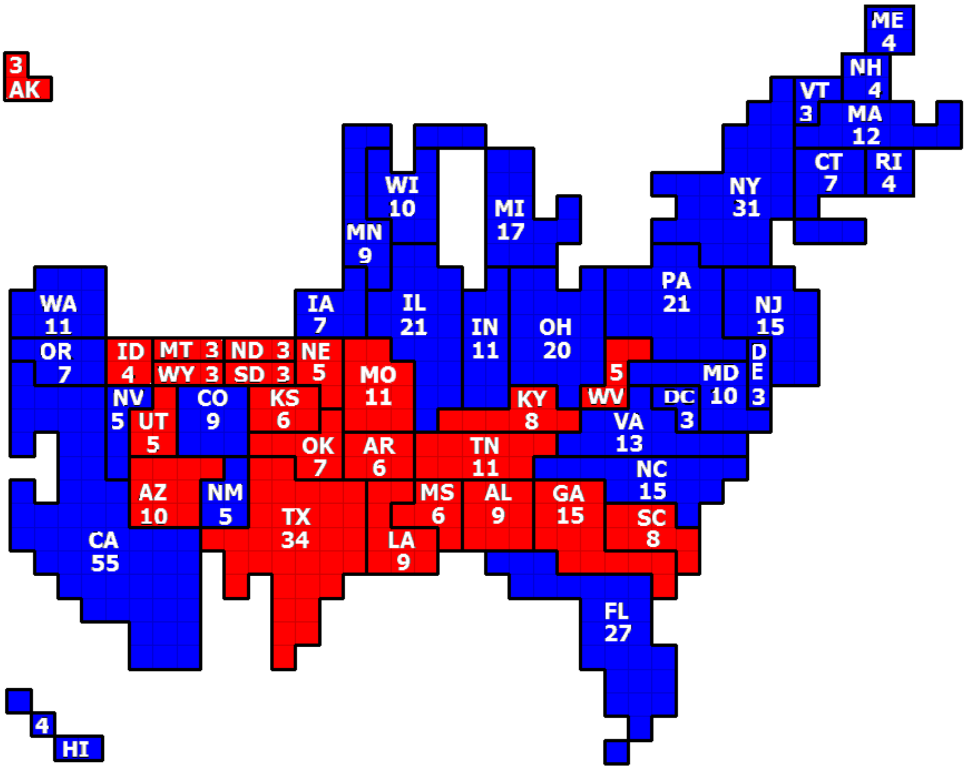

Figure 14. Map showing the electoral votes awarded to John McCain (red) and to Barack Obama (blue) by the fifty U.S. States plus the District of Columbia. In this map, states are represented by areas proportional to the number of electoral college votes to which they are entitled. About 68% of the map is blue, because about 68% of the electoral votes went to Obama. Adapted with permission from Carter (2008).

Another approach to showing the density of data on maps is the so-called "heat map." A heat map represents values by colors selected from a color ramp. Interpolation is used to estimate the value at points where no data is observed; the coloring is typically performed without reference to political or other interior boundaries. Figure 15 depicts predicted Lord's Resistance Army (LRA) activity in a given area based on previous attack data. Darker colors (within the lighter area) indicate regions of higher probability of future attacks and points show LRA attacks reported after the original prediction was created and disseminated (McCue, Hildebrandt, & Campbell, 2012).

2.3.4. Altitude, time, and animation

Although shapefiles can hold altitude or elevation data, other formats are used more commonly. These include the U.S. Geologic Survey's Digital Elevation Model; its successor, the Spatial Data Transfer Standard; and the military's Digital Terrain Elevation Data. All of these formats were developed to support the display of actual ground elevations and do not seem to be used widely to represent non-geographical data such as population densities, although some exceptions are mentioned below.

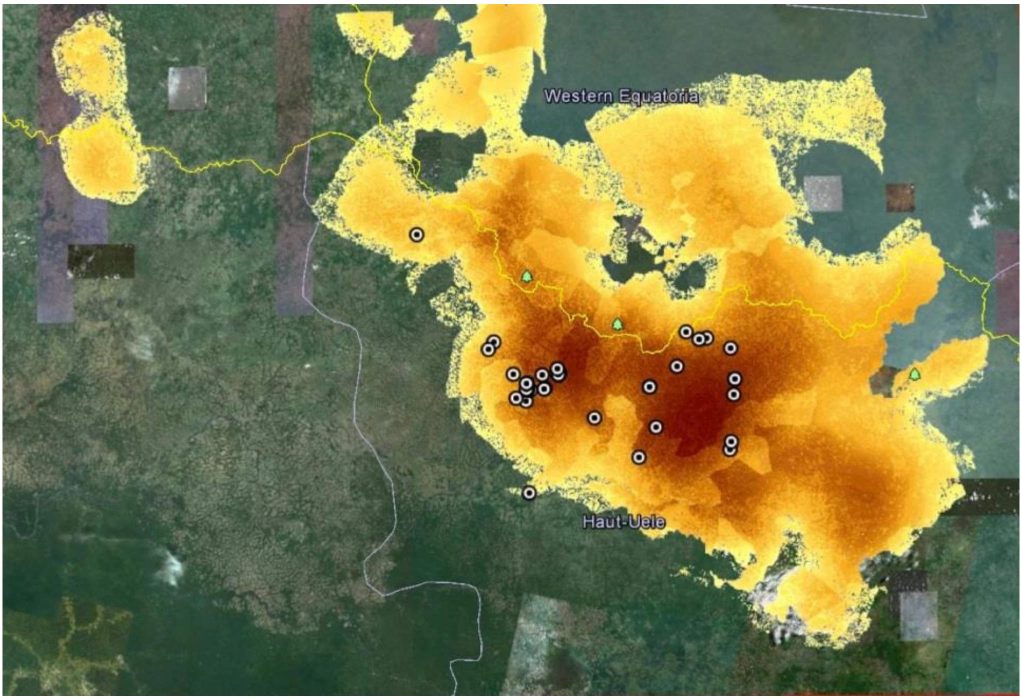

Figure 15. Heat map showing predicted Lord's Resistance Army (LRA) activity in a given area based on previous attack data. Darker colors (within the lighter area) indicate regions of higher probability of future attacks and points show LRA attacks reported after the original prediction was created and disseminated. Adapted with permission from McCue et al. (2012).

It is also difficult to display changes associated with the passage of time on a static map. Animation offers a natural tool here, and many GIS and other products make it straightforward to create a simple animation as a GIF or PNG file. These formats can be viewed in any web browser, and the resulting animation is easily understood by an audience. However, difficulties arise from the necessity of creating, storing, and displaying animations for all possible combinations of hardware and software. More important, even today a large number of readers still use paper to comprehend and store visualizations.

The simplest way to show the passage of time is by showing multiple copies of the map, each constructed using data for a different time period. For example, Figure 16 shows the number of nurses per 10,000 residents for each county in Missouri at six different time periods (Courtney, 2005). Of course, the focus on counties could lead to the same misinterpretation as in Figure 13: the independent city of St. Louis, which is very populous but is not part of any county, is nearly invisible, and the density scale is per 10,000 residents, not (as perhaps it should be) per square mile. Still, this sequence of maps makes it easy to track the status of specific counties from year to year. The smaller state map above each larger one shows which counties were declared to be HPSAs (Health Professional Shortage Areas). They reveal that the set of HPSAs remained mostly constant between 1991 and 1999, but that a big change occurred between 1999 and 2001.

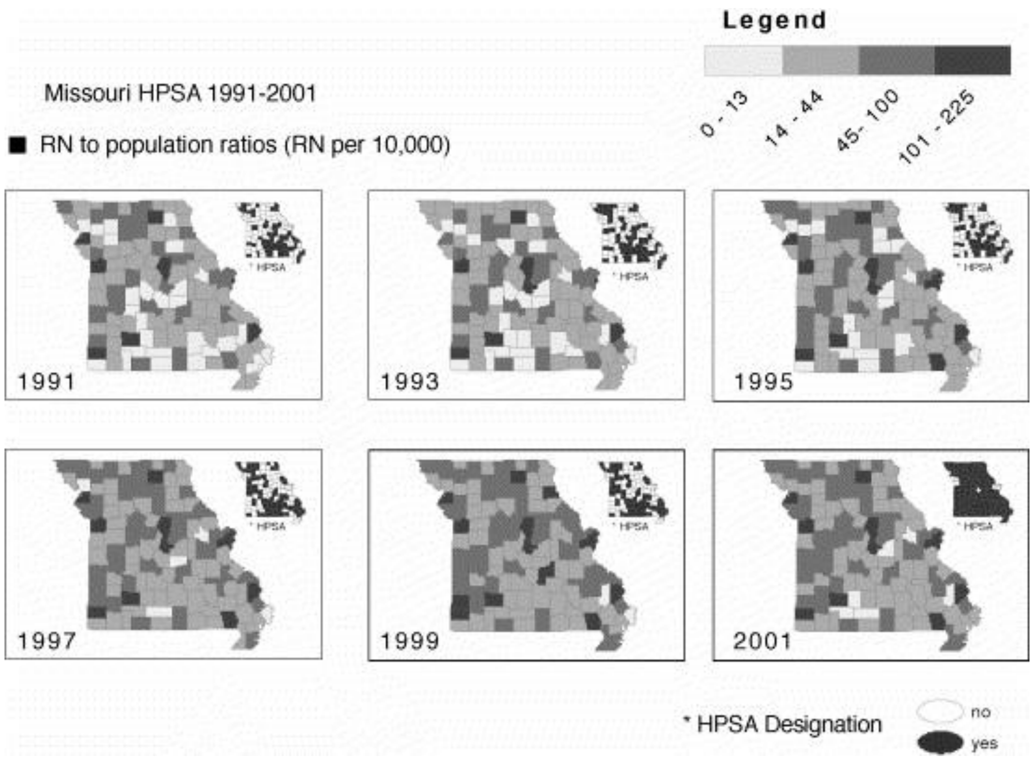

Figure 16. Maps of the density of nurses, by county, in Missouri, 1991–2001. The insets show the set of counties designated as Health Professional Shortage Areas. Adapted with permission from Courtney (2005).

We offer two more notes on this picture. First, Courtney (2005) divided the density scale of nurses per 10,000 people at values of 13, 44, and 100. Analysts can of course choose their own cutoff points, but they must make sure that (a) the graph tells the story they want to tell; (b) a different choice of cutoffs would not tell a radically different story; and (c) where applicable, the cutoffs correspond to natural or important divisions. For example, in monthly data, 6, 12, and 24 are natural divisions, whereas in income data natural divisions would be even thousands or tens of thousands of dollars. Second, the color choice in this example lends itself nicely to printed reproduction (even in black-and-white as printed here), but bright colors that are very different on a color computer screen are often similar in print. Thus, analysts must choose colors wisely, using intensity as well as hue, and perhaps with some sensitivity to the fairly common red-green form of color blindness.

As a final example, we present a map showing the concentration of arrests for prostitution in the city of San Francisco in 2009. Figure 17 (McCune, 2010) makes it easy to see that arrests in that year were concentrated in two geographic areas. The author notes that the data was "...aggregated geographically and artistically rendered. This [visualization] is meant more as an art piece than an informative visualization" (McCune, 2010, para 11). While the tools to create visualizations like

these, complete with lighting and shadow effects, are apparently not yet in widespread use, the pictures may serve to indicate current possibilities in the field of geographic visualization.

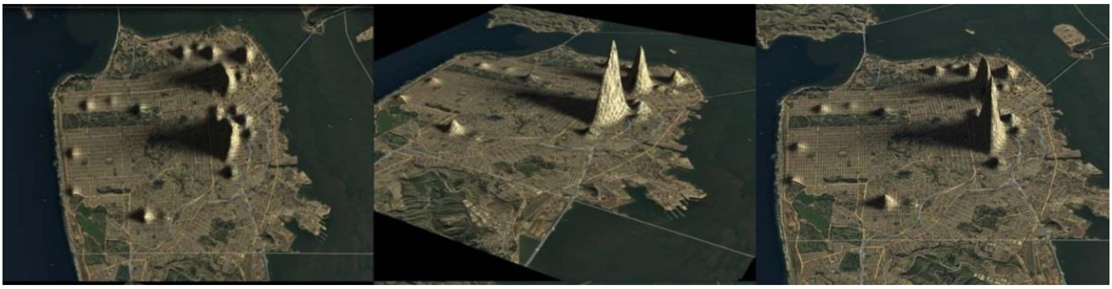

Figure 17. Visualizations of the density of prostitution arrests (vertical direction) in San Francisco in 2009. Adapted with permission from McCune (2010).

2.4. Visualization of Survey Data

Methods to visualize survey data have changed little in the past few decades, and the standard techniques of Section 2.1 apply whether the data is collected for sociocultural analysis or other reasons. One challenge emerges because survey data are typically discrete, often arising as responses to Likert scale questions. Standard displays of such data include pie and bar charts, even though these types of graphics do not lend themselves to much more than univariate presentation. These types of graphs have little utility for displaying interactions between variables or relationships among multiple variables. Even with side-by-side and stacked bar charts, users generally find it cognitively difficult to draw comparisons between subsets of the data and thus to identify complex sociocultural signatures.

The diverging stacked bar chart developed by Robbins and Heiberger (2011) represents a recent advance in survey data visualization. As shown in Figure 18, the diverging stacked bar chart centers the stacked bars, typically on the neutral or central response, and then each end of the bar diverges from the neutral. These types of plots make comparing response distributions between subsets of the data relatively easy, clear, and intuitive.

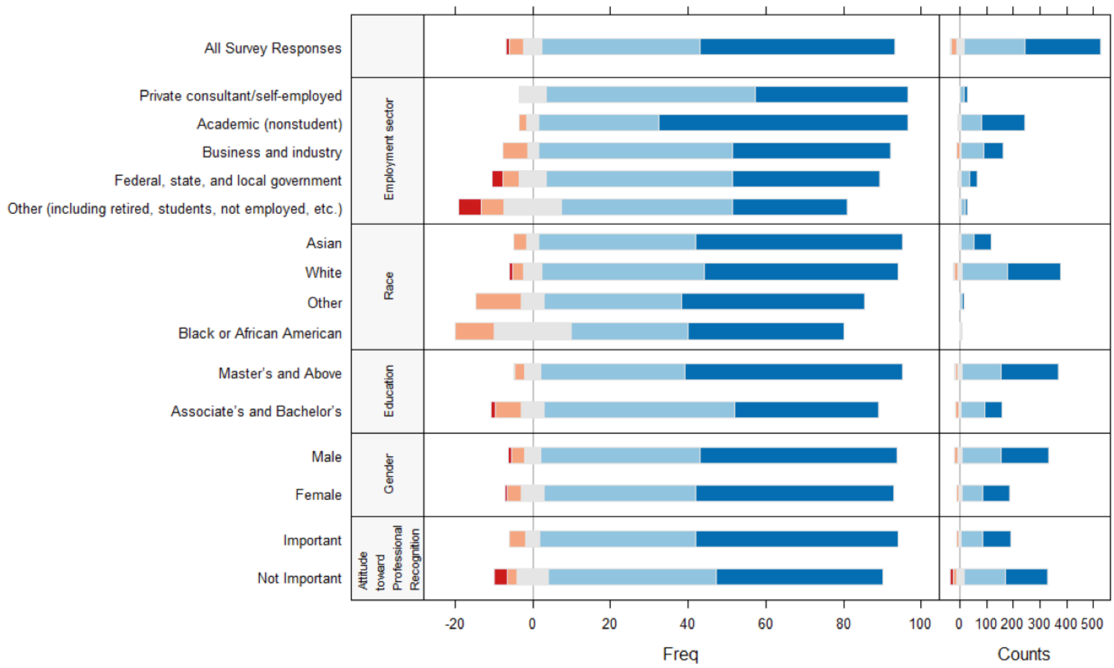

Figure 18. Diverging stacked bar chart for a five-point Likert scale question. This example shows the results for the entire sample (top bar) and then by five different demographic variables. The left set of bars shows the data in terms of percentages and the right set shows the counts. Adapted with permission from Robbins & Heiberger (2011).

A major impediment to displaying survey data collected using complex sampling designs is the lack of software that would aid in exploratory data analysis, particularly software that would allow social scientists to visualize the data easily (yet correctly and appropriately). Specialized software, such as SAS, SPSS, Stata, and R, has these capabilities, but also requires specialized skills and capabilities. Rix and Fricker (2012) proposed a proof-of-concept solution, but to date no dedicated software solution specifically facilitates visual EDA of complex survey data. At issue is that complex sampling designs require sophisticated techniques in order to analyze the data correctly. These methods must be an integral part of the software, but they also must be relatively transparent to the user, while the software also must be designed to support effective EDA, as described in section 1.2.

An open research question regarding survey data that have a geographic component concerns how to map the data *and* simultaneously show the margin of error by geographic region. The difficulty comes about because this type of visualization requires four dimensions (two for the map itself, a third for the measure of interest, and the fourth for the margin of error). Most geographic displays of survey data display only point estimates by shading or coloring regions (similar to Figures 13, 14, and 16). The need to display the margin of error as well follows if an EDA system, such as the one described in the previous paragraph, were used to display survey data geographically and allow for

"drill down" into successively smaller geographic regions. As users look at successively smaller regions, or smaller sample sizes, the margin of error increases, and the display must give some indication of this increasing uncertainty in the observed estimate.

We are currently conducting research into this issue and are performing experiments to understand which designs and design elements work best at conveying this type of information. The goal is to produce a visualization that appropriately communicates the information without much study—one that is intuitively understandable to the average consumer of the information. Figure 19 illustrates one likely solution, in which the color levels reflect the point estimate values (as is the convention with showing survey data on maps) and the uncertainty is displayed via the textures. For this example, larger hexagonal shapes represent higher uncertainty in the color value and smaller shapes represent lower uncertainty (where the lack of texture indicates no uncertainty).

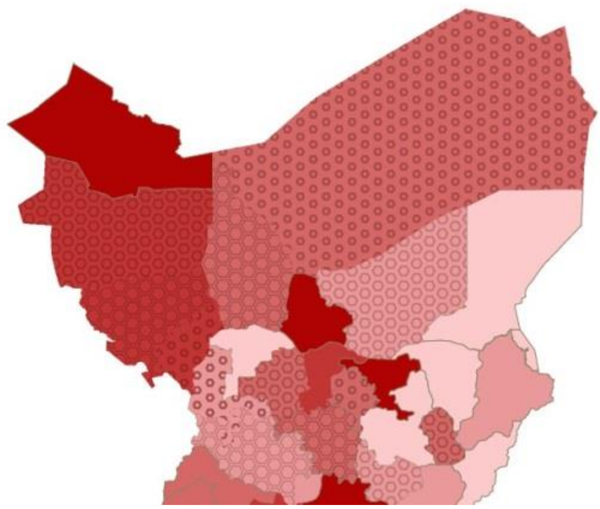

Figure 19. Illustrative map that displays survey results using color and uncertainty (the margin of error) using texture.

Finally, it is important to note that, while this discussion has focused on the visualization of survey data, accounting for how respondents visually interact with self-administered surveys is critical for good data collection. After all, there is no point in stressing good visualization of data if that data was collected poorly. Dillman, Smythe, and Christian (2009) and Couper (2008) offer visual design guidelines for paper- and web-based surveys, respectively.

2.5. Visualization for Linguistic Analysis

Linguistic data—free-form text from literature searches, survey responses, incident reports, product descriptions, web pages, blog posts, and a multitude of other sources—is as difficult to analyze as it is widely available. Although years of work have gone into methods of analyzing text,

this field is still immature. Unlike structured data, linguistic information is often complex, subtle, or even ambiguous, with interpretation depending on the reader's advance knowledge.

Natural Language Processing (NLP) and computational linguistics represent the two major directions of linguistic analysis to date. A third area, keyword search and retrieval, is well known to users as the foundation for web searches. This technique is, at least currently, more mechanical and less analytical. As a simple example that shows both the limitations of keyword search and the sorts of difficulties facing researchers using linguistic data, consider the two sentences "Emperor Napoleon drove his men towards Moscow in 1812" and "Four years into the Peninsular War, General Bonaparte led the French army into Russia." These express almost exactly the same idea, and every reader knows that "Emperor Napoleon" and "General Bonaparte" refer to the same person, but because the two sentences use no words in common, retrieval techniques will not detect their similarity.

NLP is the study of extracting meaning from text, perhaps by identifying parts of speech, named persons or places, or key phrases. Computational linguistics examines the statistical properties of a large group of documents. These might include, for example, frequency distributions over a set of important words. The two approaches differ somewhat , but from the end users' perspective, they both perform the same set of tasks on documents. These tasks include classification (of documents into groups with known content, e.g., spam detection), clustering (assignment of documents into groups of similar items), and sentiment recognition (determining whether a set of blog posts, say, shows a general approval or disapproval of a person or idea).

We should note here that our discussion, like much research in language processing, focuses on materials in English, and that analysis of English-language text generally involves a number of pre-processing steps. The first is the removal of "stop words": that is, words that do not necessarily carry inherent meaning, such as "the," "of," and "at." (Of course, stop words are sometimes important, as when naming the band The Who or preserving phrases such as "To be or not to be.") A second pre-processing step is "stemming," which removes varying word endings so that, for example, "weapon," "weapons," and "weaponry" are all reduced to the same word. In this step irregular forms such as "bought" might also be converted to their regular forms. In languages with upper- and lower-case letters such as English, words are normally all converted to one case. These pre-processing steps are almost always performed early in the analysis process by dedicated software provided with suitable word lists. Pre-processing for other languages may, of course, be quite different, although certain steps—for example, the removal of very rare or very common words—may be necessary in any language.

As a final preliminary, we observe that many of the techniques for analyzing and visualizing linguistic data require measures of similarity or "distance" between documents (Weiss, Indurkhya, Zhang, & Damerau, 2005). These distances must be computed—a process generally performed inside software. For our purposes, we can think of these techniques as representing each document in two- or three-dimensional space. The analysis then proceeds from there.

There is no shortage of tools for acquiring and processing text. Krallinger and Valencia (2005) list several dozen in the field of molecular biology alone. The medical and biological fields seem

particularly rich in research in this area, perhaps because of the large volumes of literature they generate. By contrast, techniques specifically for visualizing text seem to be in their infancy. Instead, visualizations exploit existing approaches for the tasks at hand; for example, a simple histogram might show word frequencies.

The system ThemeRiver™ forms a sequence of histograms to depict the changing distribution of keywords in a series of documents over time. Figure 20 gives one example, taken from Havre, Hetzler, Whitney, and Nowell (2002). The horizontal axis shows time from November 1960 to June 1961, and the vertical scale shows the number of occurrences of various themes in the speeches, interviews, and articles of Fidel Castro. (The thematic content was apparently extracted manually.) The different colors/shades represent the different themes, with each band's thickness proportional to the strength of that theme.

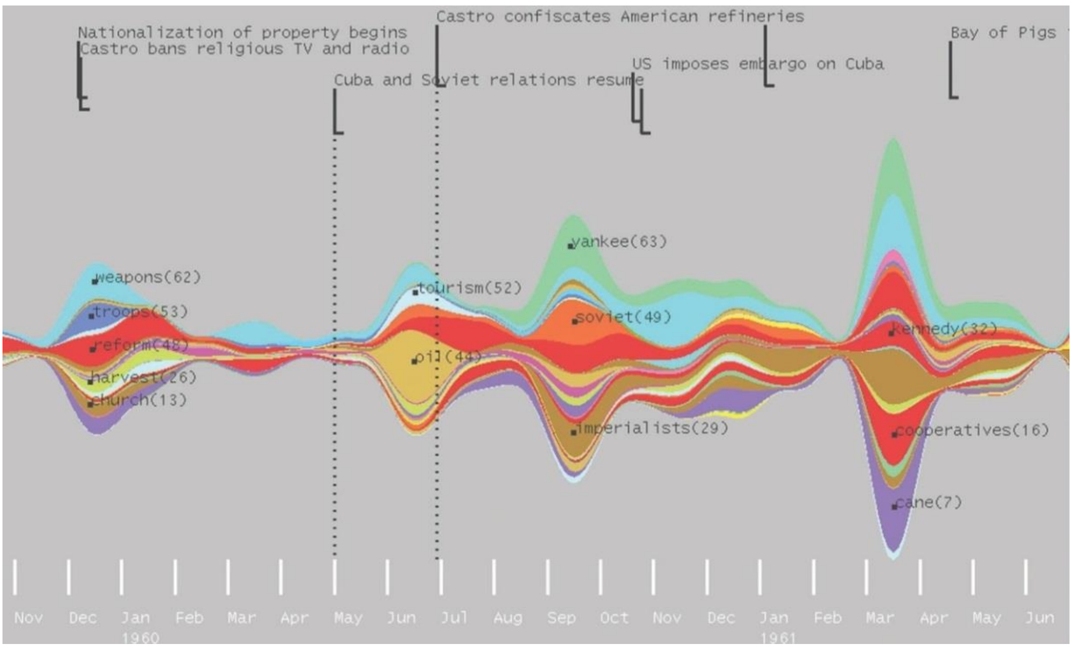

Figure 20. A "Theme River" showing the strength of a set of thirteen themes in Fidel Castro's speeches, interviews, and articles from November 1959 to June 1961. Adapted with permission from Havre et al. (2002).

Perhaps the most common text mining task is clustering. When the number of documents is small these cases often include a tree diagram (or "dendrogram"). For example, in Figure 21 Fleuren et al. (2013) used the publicly available CoPub tool (Fleuren et al., 2011) to cluster abstracts from the Medline database that related to insulin resistance, together with the authors' additions of categories (large letters, "Blood," "Cancer," etc.). (We note that the graph is difficult to read even in the original, and that the numbers relate to part of the analysis that is not directly relevant here.) This technique of hierarchical clustering involves measuring the "distance" from each document to

all the others, and then successively joining whatever pair of documents or clusters are closest together.

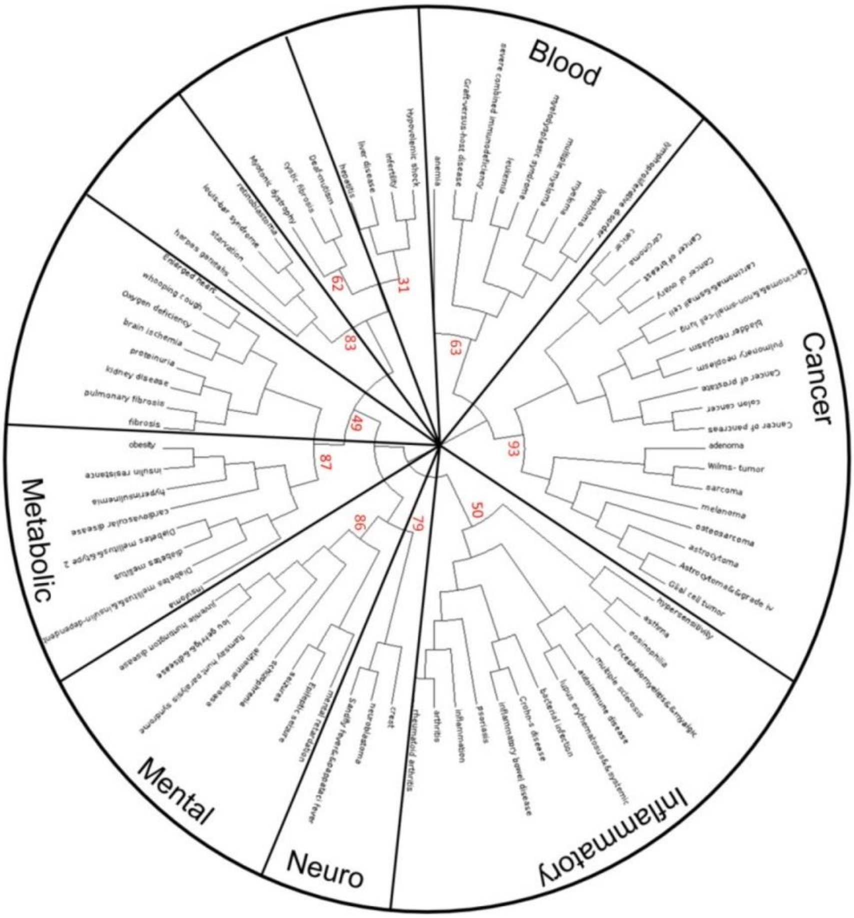

Figure 21. Hierarchical clustering from Medline abstracts. Each document is provided with a "distance" to all others; then the clustering joins documents and clusters according to distance. Adapted with permission from Fleuren et al. (2011).

A second, widely used form of clustering is partitioning, of which the well-known *k*-means approach provides an example. This, too, has been applied to documents with some success. One interesting example comes from Skupin (2004), where a corpus of some 2,200 conference abstracts was divided into 25 clusters using *k*-means. The left panel of Figure 22 shows the positioning of the documents along two axes (it is not entirely clear what those axes are); the cluster boundaries would divide the panel up into 25 pieces, if they were shown. The colors in the original plot, taken from standard geographical mapping, show the density of documents found in each region of the

cluster space; thus, many documents cluster near the labels "management" and "land" at the upper center of the picture. (The labels, it should be noted, are placed automatically, using algorithms like the ones used in GIS to prevent overlap.) In the right panel, the author has performed what he calls "semantic zooming." It shows a portion of the left panel on a magnified scale, but uses 100 clusters, presumably producing a finer level of detail. Analysts can use this technique to interact with this type of map to locate areas—that is, sets of documents in the original corpus—of particular interest. The commercial product ThemeScape produces maps like these, which it calls "content maps."

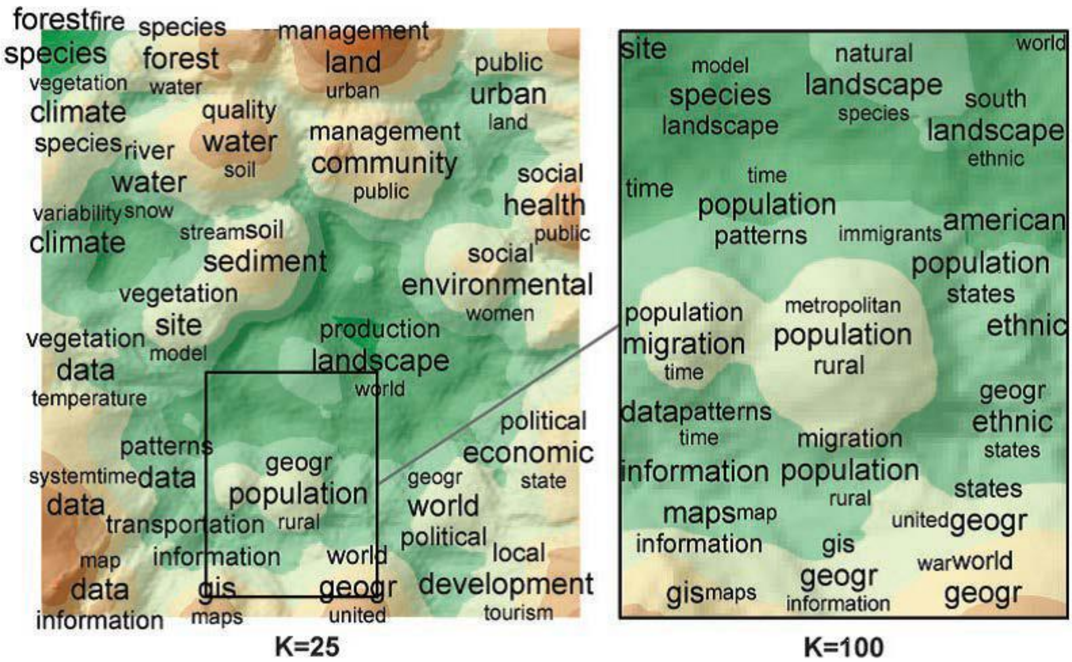

Figure 22. K-means cluster results of 2*,* 200 abstracts. The left panel shows the division of space into 25 clusters (boundaries not shown), on top of which document densities and keywords are shown. The right panel shows a sub-portion of the same region divided into 100 clusters. Adapted with permission from Skupin (2004).

Rather than cluster documents, it is possible to represent them directly—for instance as points in a high-dimensional space whose axes might represent the frequencies of certain keywords. As a concrete example, suppose we score each document based on the number of occurrences of the words "cancer," "lung," "emphysema," "bone," and "fracture." Each document could be drawn as a point in a space with five axes, where each axis might measure the number of times the corresponding word appears. A more common approach is to assign weights to words in a document according to how frequently they appear in that document and in the whole set of documents. The statistical techniques of multidimensional scaling provide a way to reduce the dimensionality of a set of points onto a two-dimensional plane (or into three dimensions), while

preserving the distances between them to the greatest extent possible. Examination of the two-dimensional projection can then yield insight into the structure of the original five dimensions.

Of course, the dimensionality of the original data might be very much higher than the five in our example. Figure 23 shows an example from Lopes, Pinho, Paulovich, & Minghim (2007). Here the authors have represented a set of 574 articles on three subjects in a high-dimensional space and then projected those points into two dimensions. (The labels in the rectangles can be ignored here.) The authors colored the points manually, according to the subject of the document. The number of mismatches (blue points in mostly red areas, for example, which may not be visible in the black-and-white figure reproduction) is small, suggesting that this technique could lead to useful rules for detecting content.

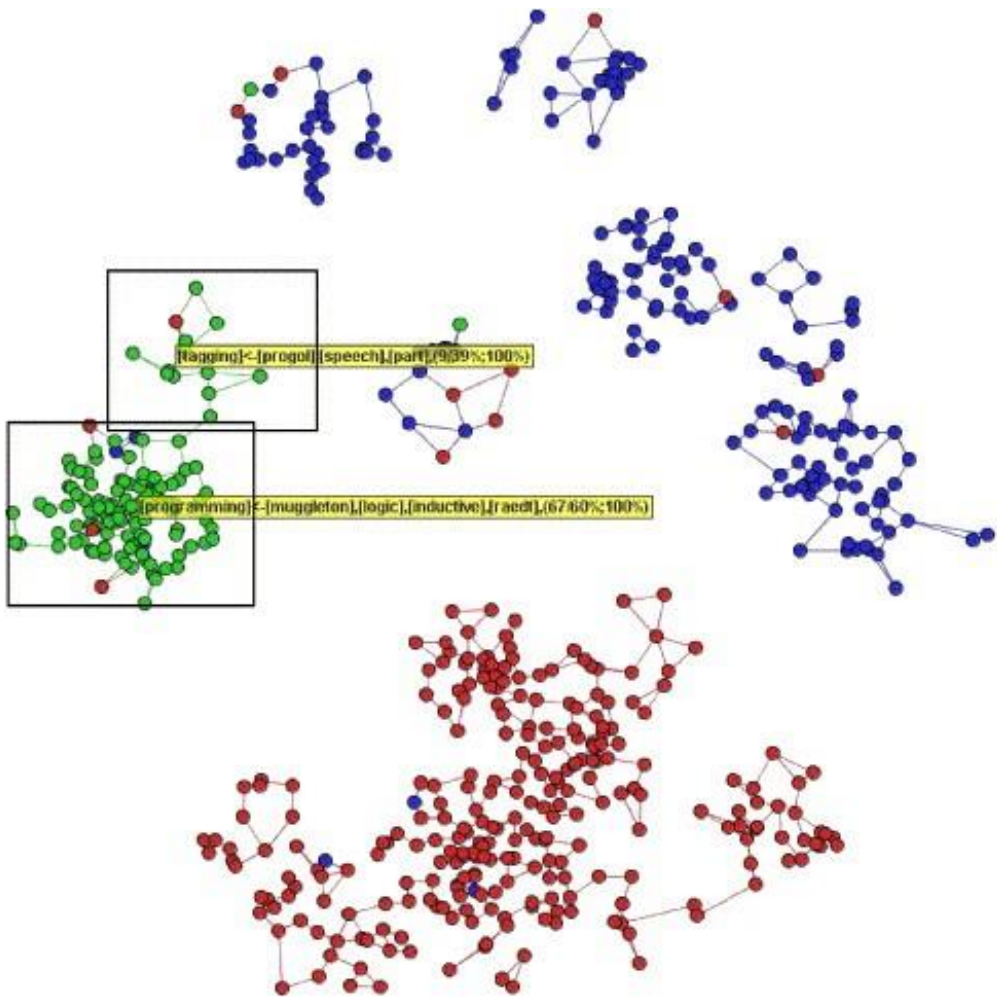

Figure 23. Example of multidimensional scaling. Points from a high-dimensional space built on keyword frequencies are projected into two dimensions in a specific way, producing obvious clusters in content. Adapted with permission from Lopes et al. (2007).

One visualization specific to linguistic data is the word cloud (or "wordle"), used to "to present a visual overview of a collection of text" (Viégas & Wattenberg, 2008, p. 49). In particular, words that appear more frequently in the text appear more prominently in the cloud; the cloud-building software arranges placement and orientation. Figure 24 illustrates a word cloud created from the NPS Operations Research Department's application for the INFORMS Smith Prize. The prize is awarded to an "academic department or program for effective and innovative preparation of students to be good practitioners of operations research, management science, or analytics" (INFORMS, 2013). The word cloud in Figure 24 clearly shows the story the department told in its prize application: students and faculty collaborating on research and practical applications. This is the point of the prize and the department subsequently won it using this application. When rendered on some sort of electronic media, word clouds can be made three dimensional, rotating, and/or interactive. Of course, no formal analyses are associated with a word cloud: the cloud is the end result. Russell (2011, Chapter 9) provides additional discussion on this topic.

HSCB data is often "streaming," that is, produced continuously over time. For example, social networks, news aggregators, and blog feeds can produce large amounts of data whose character can evolve over time or change suddenly. While some work has been devoted specifically to mining streaming data (for example, Aggarwal & Zhai, 2012, Chapter 6), this, and the associated visualization, remain very much an open field.

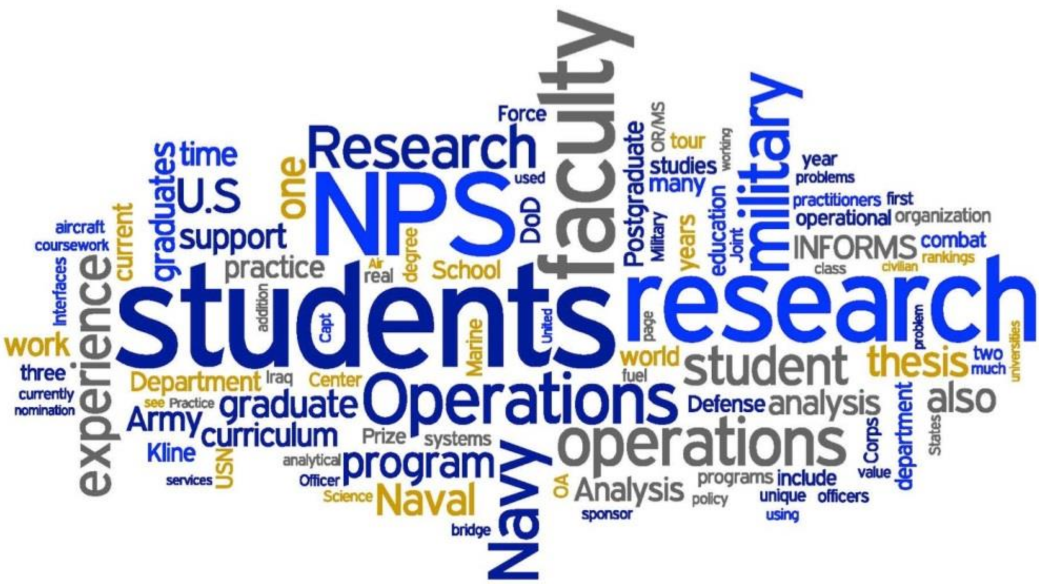

Figure 24. Illustrative word cloud. Adapted with permission from INFORMS (2013).

2.6. Visualization of Twitter and Other Social Media

Social media data can take many forms, and thus many visualizations are possible, including all of those already discussed. Typically the data is text based, but that text can arise in a large number of contexts: tweets, search engine queries, blogs, e-mail, websites, etc. The data may be cross-

sectional, in the sense that they are essentially fixed and change little over time, or temporal and perhaps highly dynamic. As social media data, they are frequently dyadic, meaning they arise as an interaction between two individuals, organizations, or entities.

If the social media data do contain information about interactions, they can often be analyzed and visualized as a network. For example, Schroeder, Everton and Shepherd (2012) used network visualizations to explore what occurred on Twitter during the Egyptian protests of 2011. To understand which users were significant conduits of Twitter information, they analyzed over one million tweets about Egypt from just two days: January 28 and February 4, 2011. They say:

> Using these data, we generated a user-by-user network [Figure 25] where a direct tie was drawn between two users if one of the users sent a message to the other, or a user retweeted the message of another. In the case of the latter, we drew a tie from the author of the original message to the user who “retweeted” the message. In the end, our user-by-user network included 196,670 users with 526,976 ties between them (Schroeder, Everton & Shepherd, 2012).

However, as discussed in Section 2.2 and as shown in Figure 25, simply plotting an entire network frequently provides little information. Indeed, Figure 25 is really just another “hairball” network visualization in the spirit of Figure 7. Thus, the authors applied an algorithm developed by Blondel, Guillaume, Lambiotte, and Lefebvre (2008) to identify distinct clusters (or communities) within the network based on the partition of users that yields the highest modularity score. As shown in Figure 26, the algorithm located several distinct clusters in the data, including news organization such as Al Arabiya and Al-Jazeera Arabic. The authors also found that a Hosni Mubarak parody account was quite central and speculated that its tweets may have been influential in framing Egyptian grievances during the revolution (Schroeder et al., 2012).

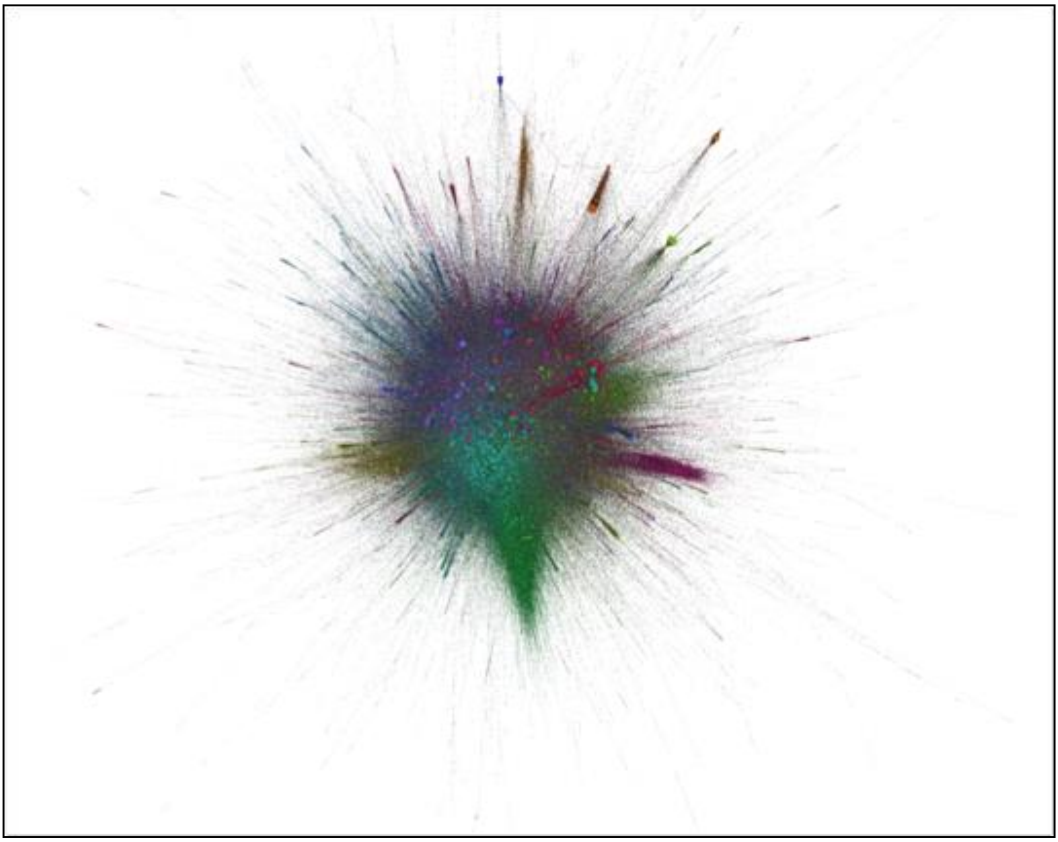

*Figure 25***.** Network visualization of tweets during the Egyptian protests for Twitter data for January 28 and February 4, 2011. Adapted with permission from Schroeder, Everton and Shepherd (2012).

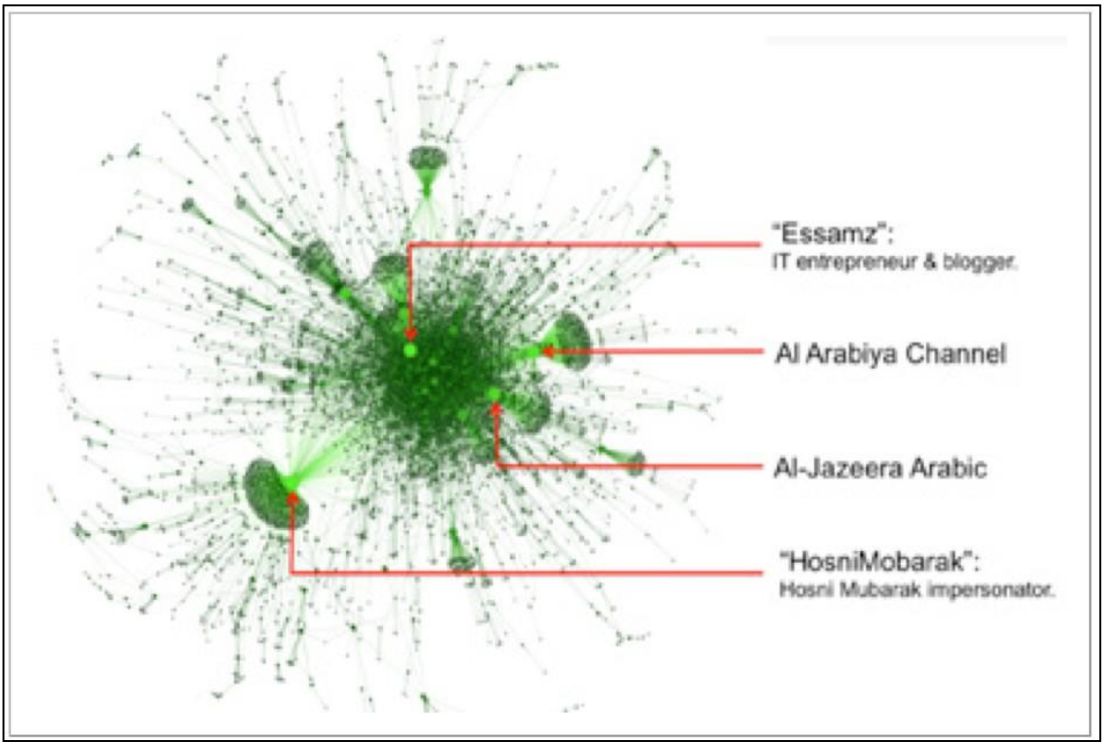

Figure 26. Alternate visualization of the tweet network after clustering users via an algorithm developed by Blondel et al. (2008). Adapted with permission from Schroeder, Everton and Shepherd, (2012).

When examining a corpus of information, which may be sets of documents or other types of social media information, analysts frequently wish to identify similar items. To this end, Figure 27 illustrates a visualization of some Google+ activities using the Protovis software[8] (Stanford Visualization Group, 2010) showing the similarity between pairs of activities (Russell, 2011, Chapter 7). In the figure the arcs indicate a linkage (similarity) between nodes, which are the Google+ activities, and the nodes are scaled according to their degree. The software sorts the nodes to minimize visual clutter and the diagram clearly shows which nodes have the largest number of connections. Note that the diagram is designed to be interactive; online the titles can be omitted because they are displayed when users mouse over the associated node. In addition, clicking on a node opens a new browser window that contains the activity represented by that node.

[8] Protovis has been supplanted by D3.js (Bostock, 2012), which provides improved support for animation and interaction, but the software is still available. D3.js builds on many of the concepts in Protovis.

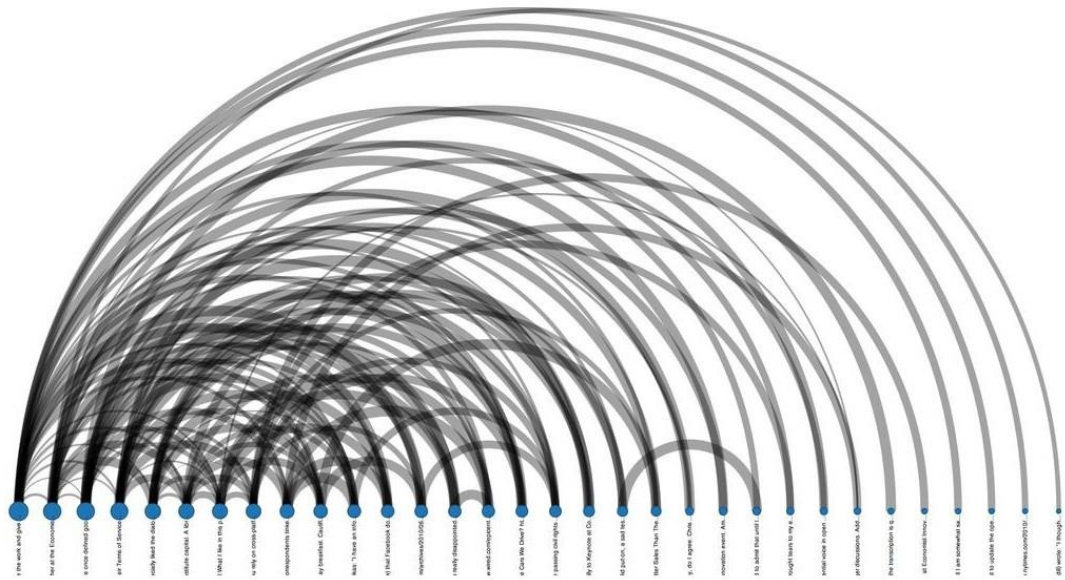

Figure 27. Visualization of the similarity of some Google+ activities. Adapted with permission from Russell (2011).

As previously discussed, signature detection may involve determining, deriving, or otherwise looking for sociocultural signatures or it may involve observing particular signatures to detect if and whether they change over time. Servi and Elson (2013) have tried to detect changes in the mood of social media users. Their method combines Linguistic Inquiry and Word Count (LIWC, 2013) with a mathematical algorithm to follow trends in past and present moods and detect breakpoints where those trends changed abruptly. The results are then plotted, as in Figure 28, to show mood changes over time. Assuming that the underlying statistic can be characterized probabilistically, this type of temporal change point detection can be further enhanced by employing methods for statistical process control based on industrial quality control. For example, see Figures 14–16 in Chapter 5 of this book.

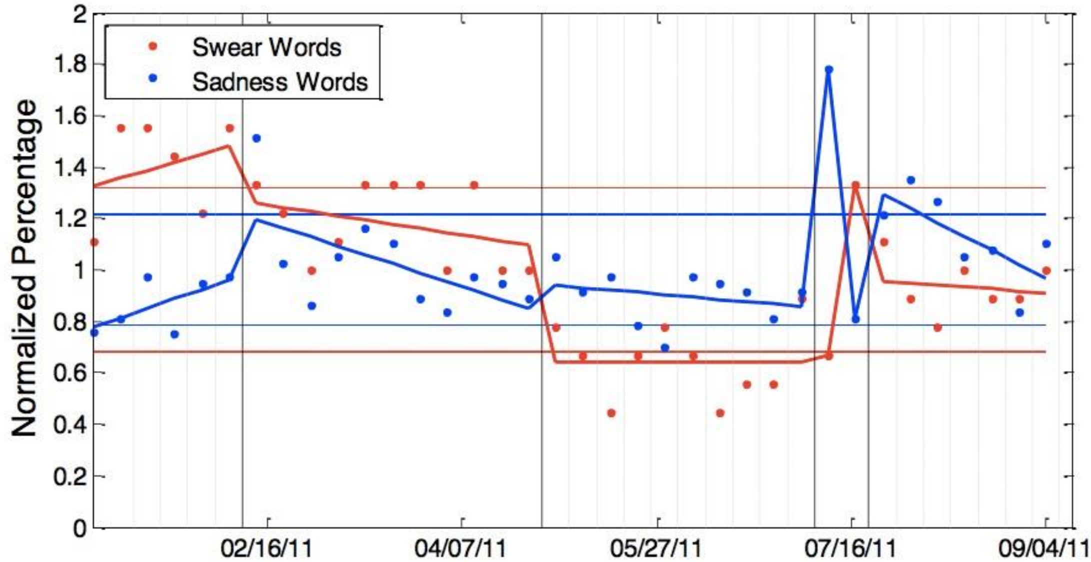

Figure 28. Visualization of Twitter mood change points, where changes are evident at (at least) four points during the displayed time period. Adapted with permission from Servi and Elson (2013).

Figure 29 illustrates another type of temporal display that is interactive when viewed online. This particular example shows a visualization of events leading up to and just after President John F. Kennedy's assassination (Huynh, 2013). The top portion of the plot shows minute-by-minute event detail from 11 am to 1 pm on November 22, 1963 (note how the time scale changes depending on the amount of detail) whereas the smaller bottom strip puts those two hours in the context of a timeline that extends from October until about 6 pm on that fateful day. While not a plot of social media *per se*, the generalization of this type of plot to social media data is obvious. See, for example Russell (2011, Chapter 3), where the timeline is applied to e-mail data.

Analysis of social media can also focus on social media metadata. For example, Figure 30 is a word cloud (similar in spirit to Figure 24 but different in layout) of Flickr's most popular photo tags. As discussed in Viégas and Wattenberg (2008, p. 50) the Flickr "tag cloud" provides "an instant overview of the site's pictures."

Donath (2002, p. 49) makes the argument that "all visualizations will have some evocative quality. We do not think in pure abstractions; rather, our thinking is metaphoric and grounded in the spatial world." Thus, good visualizations fit with our naturally developed intuitions. For example, in Figure 31 Donath (2002) uses a garden metaphor, based on the work of Xiong and Donath (1999), to visualize participation on a message board. In this "PeopleGarden" each individual participant is represented by a flower. The longer participants have been involved in the message board, the longer the flower stem, while the more they have posted to the message board, the more petals on their flower. Initial postings are depicted in a different color from replies.

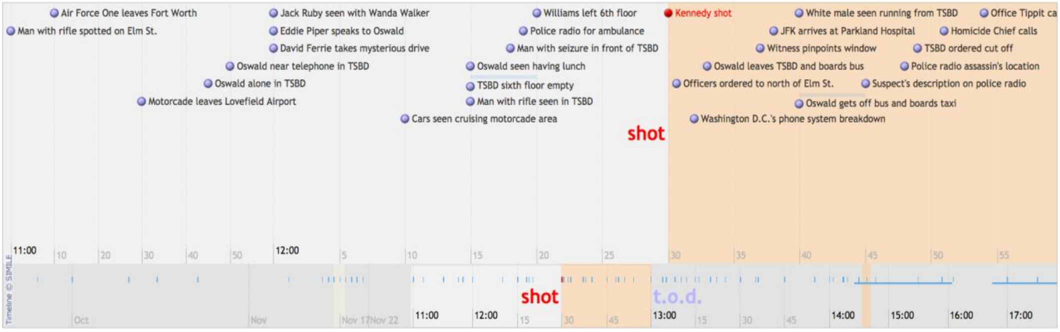

Figure 29. SIMILE timeline visualization of events leading up to and just after President John F. Kennedy's assassination in Dallas in 1963. Kennedy was shot at 12:30 pm and pronounced dead ("t.o.d." on the plot) at 1 pm. Adapted with permission from Huynh (2013).

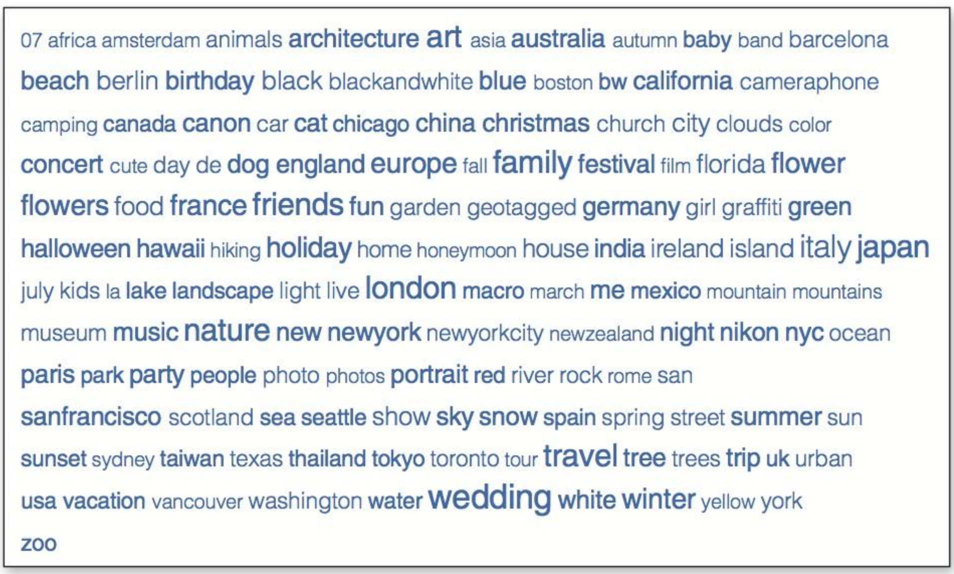

Figure 30. Example of a tag cloud visualization: Flickr's most popular tags. Adapted with permission from Figure 3 in Viégas and Wattenberg (2008).

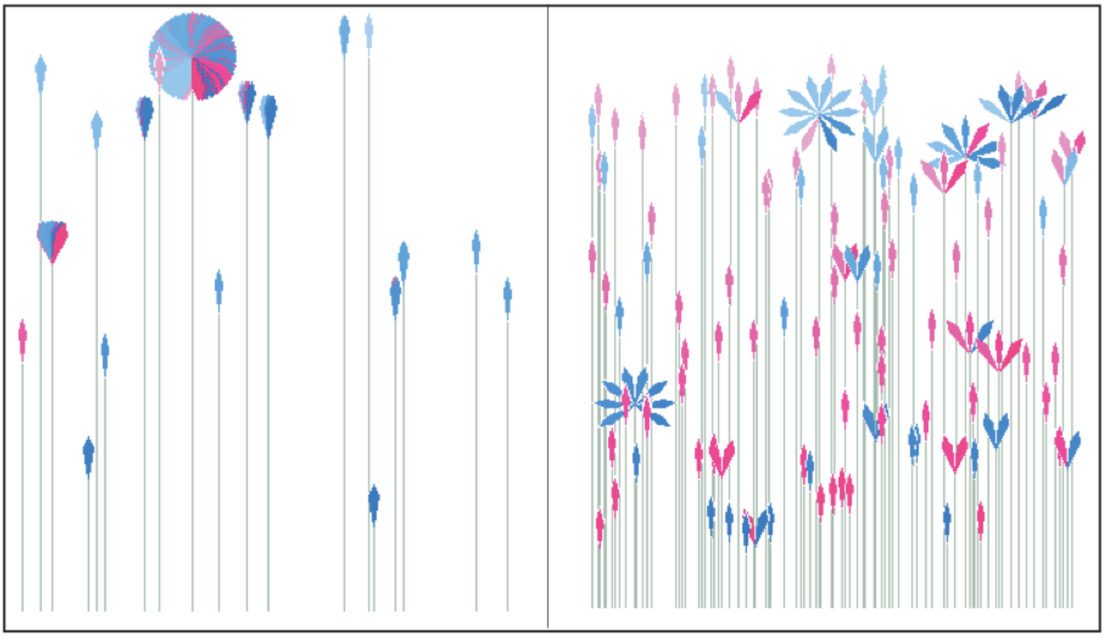

Figure 31. Example of a PeopleGarden visualization. Each flower represents a participant on a message board. Length of stem corresponds to longer involvement in the message board; the number of flower petals corresponds to the number of postings. Adapted with permission from Donath (2002).

3. Discussion and Conclusions

This chapter has focused on methods for visualizing many different types of data. Each visualization method is appropriate for a specific type of data, sometimes in a particular situation, and may be more or less useful for signature detection depending on how and when it is employed. Broadly speaking, signature detection involves identifying either differences between subsets of data, say geographically or demographically, or changes that occur over time. In this chapter we purposely emphasized exploratory data analysis because it is impossible (at least within the constraints of a book chapter) to give a comprehensive treatment of all possible strategies for detection visualization. Furthermore, while good detection strategies may be obvious in retrospect, unless the signature one is looking for is well understood and well defined, successful prospective detection will probably require the ability to explore and search through data in multiple ways.

As we have shown in this chapter, many visualization approaches are relevant to detection of sociocultural signatures. Indeed, given the limitations of the chapter, in many ways we have only scratched the surface, particularly in terms of the possible variants of the visualizations shown. Furthermore, given the ubiquitous availability of significant computing power and sophisticated software, considerable innovation is currently occurring in visualization. Some of it results in eye candy that is not particularly well suited for good information and data communication, while

other efforts have produced highly effective communication and research methods. Separating the former from the latter will become increasingly important. As Steve Jobs said,

> Most people make the mistake of thinking design is what it looks like... People think it's this veneer – that the designers are handed this box and told, 'Make it look good!' That's not what we think design is. It's not just what it looks like and feels like. Design is how it works (Walker, 2003).

Jobs's point applies equally to the design of visualization methods and to the design of Apple products. A visualization should not merely look good; it must also work well for communicating information. For additional discussions about information visualization, including open challenges, see Chen (2005) and Fayyad, Grinstein, and Wierse (2001).

While many visualization methods are widely accepted and understood, users may be unfamiliar with the new or emerging types of data visualization. Even with existing methods, users seeking to display information efficiently and effectively must understand the strengths and limitations of each type of visualization. For example, in spite of its ubiquity, the pie chart is far less well suited to visual comparisons between groups than the bar chart because human beings are better at visually comparing lengths than areas and angles (Gemignani, 2006).

A key point, as Ben Shneiderman has said, is that "the purpose of visualization is insight, not pictures" (Card, Mackinlay, & Shneidermann, 1999, p. 6). That is, any good visualization method should lead to the accurate perception and comprehension that follow when the viewer correctly understands and interprets the information encoded in the visualization. Just because a visualization looks fancy or high tech or "cool" does not mean that it communicates information accurately or efficiently. Hence, particularly when seeking to design new methods, researchers must carefully evaluate those methods to ensure they correctly convey the intended message to the viewer, as well as to identify improvements or better visualization methods.

3.1. Research Challenges

Several research challenges remain in the field of visualization, particularly as applied to detection of sociocultural signatures. Perhaps the most important challenge is simply identifying which types of signatures and changes to signatures are important to detect. Without such information, signature detection becomes an unstructured and unbounded exercise in data exploration, with a high likelihood that something "unusual" will be "detected." This brings us full circle back to the cautions raised in section 1.3 of this chapter.

Quantitatively trained social scientists often address this type of problem by, for example, distinguishing between exploratory and confirmatory hypothesis testing. In particular, they employ confirmatory methods as a guard against multiple testing that results in an increased likelihood of Type I errors. Typically this approach requires the a priori specification of one or more hypotheses that are tested against data unobserved at the time of hypothesis specification. Similarly, the a priori definition of the signatures to be detected helps to guard against Type I errors.

Of course, in many cases specifying the signatures is likely to be nontrivial and highly context dependent. However, to the extent signatures can be specified, researchers can apply visualization methods best designed or most likely to facilitate detection. An example from the physical sciences is the discovery of Pluto in 1930 by Clyde Tombaugh. Astronomers had previously predicted that there was a planet out beyond Neptune. Given its expected location:

> Tombaugh used the observatory's 13-inch astrograph to take photographs of the same section of sky several nights apart. He then used a blink comparator to compare the different images. When he shifted between the two images, a moving object, such as a planet, would appear to jump from one position to another, while the more distant objects such as stars would appear stationary. Tombaugh noticed such a moving object in his search, near the place predicted by Lowell, and subsequent observations showed it to have an orbit beyond that of Neptune (Wikipedia, 2013).

In this example, the type of available data (photographs) and the expected signature (motion against a stationary background) drove the methodology used for detection.[9]

Other research challenges may include legal and regulatory difficulties in gaining access to data in order to perform visualization; technological challenges related to designing and implementing computer hardware and software necessary to display the data in a visualization; ethical and security-related issues related to managing and safeguarding the data, particularly if it is sensitive; analytical and algorithmic challenges in developing and displaying the visualizations; and the managerial challenges of effectively assembling and operating an entire system, particularly if the visualizations are depending on massive and/or disparate data. Other chapters of this book address some of these challenges.

Finally, simply continuing to improve upon existing visualization methods is an important research challenge. Better visualizations require innovation in the way data is visually presented *and* subsequent careful evaluation of those methods to ensure that they fulfill their intended purpose. Whether or not a visualization method "works" encompasses a number of dimensions, including whether the visualization presents the information accurately, whether the viewer can subsequently retrieve the desired information from the visualization, whether the visualization is intuitive and easy to interpret, etc.

Over the years, researchers have used formal experiments and/or Darwinian selection to evaluate many of the classical visualization methods noted in section 2.1. Carpendale (2008) and Cleveland & McGill (1984), among others, offer discussions of experimental approaches to evaluate visualization methods and techniques. However, Perer and Shneiderman (2006) propose a case study approach rather than controlled experiments in a laboratory when assessing more complicated visualizations, particularly for evaluating software used for EDA and visualization. Often, for example, effective signature detection requires more than simple, static visualization; it may require a software system with an interface design that allows the user to easily and

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[9] Our thanks to an anonymous reviewer who suggested this example.

appropriately explore the data. Important features include the ability to "drill down" into the data for details (for example, to facilitate easy identification and analysis of subgroups and dynamic and interactive graphics), and to "tour" through the data, particularly higher dimensional data (Fricker, 2013, p. 109). With such systems Perer and Shneiderman (2009, p. 42) say,

> ...laboratory-based controlled experiments are less compelling for information visualization and visual-analytics (VA) research. VA systems are often designed for domain experts who work for days and weeks to carry out exploratory data analysis on substantial problems. These types of tasks are nearly impossible to reconstruct in a controlled experiment for a variety of reasons.

Ultimately the point is that, regardless of how, new visualization methods and software should be evaluated. As most, if not all, of this work is now done via some type of computer-based system, these evaluations may also extend into the realm of human-computer interaction evaluations as well (see, for example, de Graaff, 2007, and Hunt, 2013).

3.2. Concluding Thoughts

For social scientists working with sociocultural data, this is a revolutionary time to be conducting research. As Michael Macy says, "Human beings around the globe are now communicating with each other using devices that record those interactions and have open access. I think this is an extraordinarily exciting moment in the behavioral and social sciences" (Miller, 2011, p. 1814). Furthermore, the era when research data sets were small enough that one could actually look though the raw data and learn something from it is long past. Today systems capture and store data, in a wide variety of formats and types, at a rate that makes effective visualization perhaps the only way to comprehend the data. Welcome to the era of data visualization!

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8 Cross-cultural training and education for detection[1]

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1. Introduction and Overview

Sociocultural signatures are unique, identifiable (often because they are repeated) features of the social and cultural landscape. That landscape includes observable individual biometrics (i.e., characteristics or traits, such as personality profiles, fingerprints, and voice profile), as well as individual and group sentiments and behaviors (Maybury, 2010) exhibited in political, economic, and social structures.

Detection of sociocultural signatures involves more than maintaining situation awareness and identifying facts in the physical environment. It requires a deeper understanding of what those signatures mean. Sociocultural analysis helps to unravel the meanings of these signatures by decoding how and why people sense the world as they do.

As an example, one might observe that, although Brazilian officials were confident that they would be prepared for the Confederations Cup in June 2013 (a precursor to the World Cup 2014), at the time of writing this chapter, Brazil had built only two-thirds of the soccer stadiums needed by FIFA's (*Fédération Internationale de Football Association*) mandated deadline (Boadle & Downie, 2013). Sociocultural analysis might help to explain this by revealing a pattern in how processes are paced in Brazilian society. Researchers might conclude that it took Brazilian officials two years to determine which 12 cities would host the games because of the government's strong desire to generate the greatest economic benefit for the country. The cities selected could then have taken another long time to build the stadiums due to the same relationship structures being used to find the building contractors that would generate the greatest benefit for the organizers. Further, during the selection process, time was on the side of the contractors who could negotiate better prices as deadlines approached. At a macro level, Brazilians are generally more comfortable with uncertainty than FIFA officials. In fact, legendary Brazilian soccer player Ronaldo was quoted as saying, "We leave everything to the last minute" (Boadle & Downie, 2013).

This example illustrates how sociocultural analysis involves making sense of observed behaviors by accounting for relationship structures (i.e., negotiating costs and benefits) that might explain how

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sentiments and behaviors developed (i.e., "things will get done"), as well as values (i.e., tolerance for uncertainty) and beliefs (i.e., "do not do today what you can do tomorrow") that have guided individuals' behaviors in a social context.[3]

In this chapter, we discuss the importance of *cross-cultural training and education* (CCTE) as a prerequisite for robust sociocultural analysis, and recommend methodologies for trainers. We also offer suggestions to Department of Defense (DoD) policy makers who must support CCTE for civilian and military U.S. Government (USG) personnel. We first introduce a conceptual definition of culture, as well as concepts and dimensions of culture that trainers must address in CCTE. Second, we identify some gaps in current analytic practice that research should seek to fill. In the third section, we present state-of-the-art findings from cultural and cross-cultural research that could inform CCTE methods and designs, including best practices in CCTE. Finally, we put forward some recommendations for implementing CCTE more richly and effectively in operational environments.

2. What Is Culture?

Culture gives meaning and distinction to the existence of a group. The term "culture" encompasses values, norms, behaviors, and beliefs implicitly shared among members of a social system – defined as a group characterized by meaningful interactions among individuals (Schwartz, 2009). These characteristics of a culture develop and modify over time, and are reinforced by the interactions of people within it. Thus, an inherent component of understanding culture is understanding how the people within it interact and why. For this reason, intelligence professionals (IPs—a broad term that includes analysts) must focus on patterns of social interactions that provide evidence of group behaviors and *how* behaviors and sentiments develop. Starting with dyadic relationships, including person-to-person, person-to-group, and group-to-group, IPs can come to understand the more complex relationship structures that define cultures, and explain *why* dyadic relationships take a particular form.

The term "culture" is multi-layered and can be applied to describe different kinds of social systems, including regions, countries, nations, ethnic groups, and families. While many associate the concept with nationality, not all social systems correspond to national borders (McGinn, Weaver, McDonald, van Driel, & Hancock, 2008). Thus, we can refer to peer group cultures, corporate cultures, and national cultures.

Culture influences and is influenced by social, educational, business, political, economic, linguistic, legal, and religious systems (Tayeb, 1994). It is both around and within us, and individuals have cultural signatures, but people are not embodiments of culture. By analogy, simply because the United States is considered a wealthy nation does not mean that all people in the United States are wealthy. Similarly, even within a relatively collectivistic culture different individuals focus to different degrees on their duty to their families and subgroups.

Cultural syndromes—composed of norms, beliefs, and values—are often mistakenly used to assert qualities of a person. Although IPs should use these syndromes to guide understanding of a

[3] See Green Sands & Haines (2013) for another example drawn from a simulated war game.

person's behaviors, they must also seek alternative explanations on the basis of an evaluation of multiple cultural factors.

Culture manifests itself not only in the perceived physical world, but also in *how* and *why* people interact in that world as observed. Cultural differences become evident when people perceive the same stimuli—be they social or physical—in different ways (e.g., interrupting a person who is speaking might mean someone is respectfully engaged in a conversation or disrespectfully uninterested in what another person wants to say). Moreover, the consequences of the perceived stimuli differ across cultures. For example, people with similar professions in different national cultures experience different strains despite similar work stressors (Glazer & Beehr, 2005). In Glazer and Beehr's (2005) study, fewer nurses in Hungary intended to leave their jobs because of anxiety than U.S. nurses, even though the Hungarian nurses had greater work overload (leading to anxiety) than their U.S. counterparts. As this example illustrates, finding observable factors or artifacts that manifest themselves in the focal environment—such as rate of turnover—is not the end goal, but the first step in detecting sociocultural signatures. In understanding the effect of culture on this behavior, one must recognize how the behavior relates to a stimulus. In this case, Glazer and Beehr suggested that in Hungary the relationship structure between nurses is communal. Therefore, although the Hungarian nurses had greater role overload and higher anxiety than U.S. nurses, these might not provide sufficient motive for the nurses to leave their employers and put their colleagues in the precarious position of enduring even more overload. In fact, as these data came from nurses working at four hospitals in Budapest, and there were no differences on the main study variables across hospitals, it is entirely possible that moving to another hospital would yield the same outcomes.

Through sociocultural analysis, Glazer and Beehr (2005) explained the processes and underlying assumptions that led to the observed artifacts, such as identifying the communal sharing relationship structure and cultural values (harmony and conservatism; see Table 1 for definitions) associated with the detected outcome. Thus, the foundation for any CCTE activity must rest on a thorough understanding of concepts that apply throughout a given culture, which in turn will serve as the cornerstone for understanding how and why observed behaviors are manifested.

2.1. Culture-General Concepts

Culture-general concepts central to CCTE include artifacts and practices, norms, beliefs, and values.

Artifacts and Practices. Artifacts are aspects of culture that are immediately visible; they include tangible objects or observable practices. Practices are behaviors or patterns of social interactions, which in turn reflect an underlying set of rules and understandings. A group's practices are informed by the group's values and norms. Because of this, a practice may carry different implications across groups. For example, when a subordinate speaks to a supervisor, it is common practice in U.S. culture that the two maintain eye contact, as this implies attentiveness and sincerity (Hattori, 1987). In Japanese culture, however, a subordinate making significant eye contact with a supervisor is considered disrespectful or immodest (Hattori, 1987)—likely due to how highly Japanese society values hierarchy (Schwartz, 1999).

Considered together, artifacts and practices form "surface culture." After detecting artifacts and practices, IPs must consider *how* they came to be, which addresses "process culture," and *why*, which addresses "deep culture." Norms, beliefs, and values represent both process and deep cultures.

Norms. Norms include not only prescribed but also implicit and informal procedural rules to guide and regulate how people may behave (Smith & Berg, 1987), and indicate what individuals "ought to do" in a given situation (Fischer et al., 2009; Hitlin & Piliavin, 2004). Norms depend on context. In a group context, social networks both punish members for deviating from norms and reward members for upholding them (Cialdini & Trost, 1998; Fisher & Ackerman, 1998). Different cultures place varying degrees of emphasis upon adherence to social norms in general and the punishment of those who violate them (see Triandis's, 1994, "tightness-looseness" cultural dimension, defined in Table 1): some groups may allow considerable deviation from set norms, while others enforce them much more rigidly.

Beliefs. A belief is a generalized understanding of how two concepts relate to one another (Bar-Tal, 1990; Bem, 1970; Katz, 1960). Beliefs represent the fundamental organization of a worldview: "generalized expectancies" or "premises that people endorse and use to guide their behavior in daily living" (Bond et al., 2004, p. 552). The firmness of a belief can vary depending on the level of confidence in the belief's truthfulness. Beliefs are also highly variable in terms of specificity (Leung et al., 2002), ranging from very particular—referring only to specific people, events, situations, or other targets—to expansive and abstract, pertaining to a wide variety of contexts and targets.

General beliefs guide behaviors across various situations; they are what Leung et al. (2002) refer to as *social axioms*. These beliefs enable people to organize their responses to the social and physical world around them. For example, people with a high internal locus of control may be more likely to underestimate hazards in risky situations (Liverant & Scodel, 1960) because they believe that they can control the situation. Beliefs such as this also serve as explanations for the kinds of values people hold and why they observe artifacts as they do. For example, a common U.S. belief, influenced by a long-term orientation (see Table 1), is that perseverance is important. This helps to explain why U.S. citizens often continue to pursue goals even in the face of difficult odds. In the context of collection and analysis, identifying and understanding others' beliefs provides an understanding of the deeper meanings of artifacts.

Values. Values are abstract principles that people view as desirable, right, and good across situations (Hitlin & Piliavin, 2004; Schwartz, 1999). These principles motivate and guide individuals, helping them to make sense of social systems. Values are embedded in a group's norms and practices (Knafo, Roccas, & Sagiv, 2011). They facilitate the choices people make in evaluating behaviors and events, and serve as motivating factors toward goal fulfillment (Schwartz, 1992, 1999, 2009). The goals served by values relate fundamentally to biological and social survival (in terms of interactions and group welfare). Although cultures may share the same goals, the behaviors exhibited as people seek to fulfill those goals might differ across cultures; because the emphasis placed on certain values differs, behaviors motivated by the values differ. Thus, at the level of culture, values can be seen as solutions to problems faced by people in a given ecological environment.

Together, norms, beliefs, and values form a culture's dominant profile, also referred to as a *cultural syndrome*. Table 1 lists example cultural factors that contribute to cultural syndromes. Similar to an iceberg, the visible portion of a culture is small compared to what lies hidden beneath. Developing capabilities to detect hidden factors that influence the visible factors is paramount to sociocultural analysis.

Table 1. *Cultural elements and their conceptual definitions*

CULTURAL VALUES

Hofstede (2001): Cultural Values

Individualism vs. Collectivism

- Society views individuals' identities as distinct and unique to the social group (personal time, freedom, choice, and competition valued) vs. society views individuals' identities as integral and interdependent (group needs above personal needs).

Power Distance

- Society reinforces hierarchy as established by supervisor power over subordinates. It describes how societies cope with human inequality.

Masculinity vs. Femininity (aka. achievement vs. nurturing; instrumental vs. expressive)

- Society values achievement and wealth, resolution of conflict through aggression, careers for men not women, and "live to work" vs. society values placed on nurturance, environmental welfare, negotiation, women's involvement in workforce and politics, "work to live." The former deals with the development of group norms, roles, and leadership, whereas the latter deals with social networks and group decisions.

Uncertainty Avoidance

- Society lacks tolerance for uncertainty and reinforces individuals' adherence to rules and following prescribed norms.

Long-Term vs. Short-Term Orientation

- Society focuses on future through planning and saving vs. society focuses on immediate action with little consideration for implications on future.

Table 1. *continued*

Schwartz (1999): Cultural Values

Autonomy

- Society reinforces individual choices and opportunities to be unique. These societies encourage individual flexibility in thoughts, ideas, emotions, and feelings and view the person as an autonomous, bounded entity, who can legitimately change status quo and engage in stimulating activities.
    - Intellectual Autonomy
        - Society places importance on individuals' independent pursuits of desired goals and creative ideas. These societies view the person is an autonomous decision maker who engages in social exchanges based on contractual relationships. The person is encouraged to value free thoughts and ideas.
    - Affective Autonomy
        - Society places importance on independent pursuit of positive affective experiences. These societies view the person is an agent of change in the status quo and as desiring arousing/stimulating experiences, feelings, and emotions, such as excitement and desire for a varied and stimulating life.

Egalitarianism

- Society places importance on equality, opportunities for all, and providing help for the benefit of the welfare of others. These societies encourage people to be autonomous decision makers, who engage in social exchanges based on contractual and cooperative relationships and pursue prosocial activities for the welfare of others, such as social justice, peaceful world, freedom, honesty, and equality, but also accepting one's portion in life.

Harmony

- Society places importance on fitting in with the environment, avoiding change, and engaging in cooperative relations. These societies encourage individuals' unity with nature, protecting the environment, and maintaining a beautiful world.

Conservatism

- Society places importance on the status quo, modesty, fulfilling role expectations, and maintaining homeostasis of the group or the traditional order. In these societies the person is embedded in a group of interdependent, mutually obligated others. These societies emphasize that personal welfare depends on the welfare of the group. Maintaining homeostasis is paramount in these cultures. Homeostasis between and among people is achieved through modesty, utilitarian exchanges, forgiveness, and order.

Table 1. *continued*

Hierarchy

- Society emphasizes status differences and ascribed roles (Schwartz, 1994). It places importance on allocation, coordination, and differentiation of power, roles, and resources in pursuit of wealth. In these societies, the person is embedded in a group of interdependent, mutually obligated others, whereby individuals attempt to get ahead, even at the expense of others, while also maintaining respect for and distance from authority.

Mastery

- Society places importance on controlling the social environment and getting ahead through self-assertion. In these societies, the person is an agent of change and stimulating activity, often at the expense of others. The society encourages pursuit of goals, ambition to succeed, and capability of controlling one's environment, including the social environment.

Triandis (1995; 2009): Cultural Dimensions

Tightness vs. Looseness

- Society adheres to clear, strict social norms that are reliably imposed in socially accepted "important situations;" deviations are punished vs. society accepts unclear norms and has greater tolerance toward deviations from norms; sanctions are not severe and are possibly informal.

Simple vs. Complex

- Society is characterized as being scarce in resources vs. information societies, that have many human and material resources.

NORMS

Fischer et al. (2009)

Individualism vs. Collectivism

- Society reinforces personal vs. group needs or obligations as evident in socially-oriented expressions of (vs. values of) self-perceptions, relationships with others, goal orientation (for self or group), and behaviors.

SOCIAL AXIOMS

Bond et al. (2005)

Societal Cynicism

- Society reinforces a social system of generalized hostility toward its members.

Dynamic Externality

- Society reinforces a combination of religiosity, belief in fate, and a focus on effort and control.

3. Science and Technology Gaps in Cross-Cultural Training and Education

CCTE can strengthen intelligence professionals' (IPs') abilities to detect anomalies in foreign others' interactions and behaviors, and to explain the assumptions underlying them in order to forecast their implications for security and to mitigate threat. However, we have observed that IPs perceive themselves to have limited autonomy in preparing statements that consider alternative perspectives that might explain observed artifacts.

Indeed, the most prominent gap in the IP's toolkit concerns the ability to answer "how" and "why" observed cultural factors emerged. In many cases, IPs who must answer an intelligence question cannot explain how and why the answers are manifested as they are. In some cases, they may not have the opportunity because the answer to *why* is not part of the intelligence question posed. Too often, however, IPs explain artifacts on the basis of their own cultural understanding of an adversary's behaviors, rather than being able to present *why the behavior occurs as it does* from the perspective of the adversary. For example, in a recent NBC News report, Windrem (2013) reported a cyber analyst's observation that different Chinese groups engaging in cyber-hacking activities do not cooperate with each other because they do not share information. A close examination of the explanation suggests a lack of cultural understanding: the lack of sharing is *indicative* of not cooperating, but does not explain it. CCTE would help an IP recognize that this lack of intergroup cooperation is a manifestation of the cultural values for mastery and hierarchy.

> Cultural sensemaking is a collection of skills [that] enhance [sic.] and/or modify existing cultural schemas (models) of the intelligence professional. These schemas can restrict and influence an individual's decision (understanding, assessment and priority) on what data to collect, and the consequent meaning of the behavior being observed. (Green Sands & Haines, 2013, para. 2)

This kind of sensemaking does not involve applying sophisticated stereotypes (Osland, Bird, Delano, & Jacob, 2000), but instead detecting real cultural signatures in order to make sense of the situation in which an interaction occurs in a particular environment. It is also an enabler; it helps IPs make sense of the situation in which an interaction takes place, which is vital to forecasting and mitigating real-world concerns. As Flynn, Sisco, and Ellis (2013, p. 13) wrote, "the lesson of the last decade is that failing to understand the human dimension of conflict is too costly in lives, resources, and political will…to bear." Understanding sociocultural factors in context is imperative if violence is to be mitigated. According to Flynn et al. (2013), today's IPs miss the mark in detecting factors that have a major bearing on national security. They argue that IPs must develop "social radars" that provide fine-tuned explanations for observed behaviors. The term "social radar" refers to the detection of sentiments (attitudes, beliefs, and behaviors) in a focal context (Maybury, 2010). Social radar would enable IPs to detect when changes occur in the social environment (Costa & Boiney, 2012). Costa and Boiney claim that the goal of social radar is to "take a data-to-decision support perspective, allowing [IPs] to tailor and weight the fusion of indicators, draw on online sources to update model parameters, and use course of action models to provide quantitative evidence for indicator integration strategies" (p. 5).

Through this process IPs must be able to interpret detected artifacts and apply their culture knowledge to explain how and why the artifacts manifest. Thus, a major learning objective of CCTE

would be to enable IPs to develop a wide-angled cultural perspective when analyzing the actions of people who come from cultures that differ from that of the IP. They should learn to consider multiple alternative explanations for the observations. Enabling CCTE objectives include:

- Become aware of one's own cultural biases and cultural lens, that is, self-awareness
- Develop skills for self-reflection in perspective taking
- Develop skills for detecting and interpreting cultural nuances by understanding deep, process, and surface culture
- Increase awareness of communication patterns among members of a culture (e.g., task vs. relationship orientation, status, and roles).

3.1. Self-Awareness

One of the shortcomings that IPs must overcome is minimal awareness of their own cultural biases when interpreting others' behavior. Attribution bias—in which people explain their own experiences as a function of the environment, but others' behaviors as a function of their personality or personal attributes—might lead IPs to misattribute explanations to personality instead of situation and culture. Thus, the first step in enhancing intercultural interactions within the intelligence community consists of learning about or reflecting upon our own character and past experiences.

Self-awareness inventories enable people to explore their own thinking patterns and behavioral styles. These tools can serve as a springboard for thinking about how those patterns bias the interpretations of artifacts. They also provide guidance for trainers who need to understand the stage that trainees have reached in their development. Objectives associated with self-assessment are: (a) provide instrumented feedback to individuals regarding their self-construals, values, and level of intercultural competence, (b) introduce training concepts, (c) supply non-threatening vocabulary, (d) serve as a frame of reference, (e) teach trainees to appreciate the strengths and understand the limitations of people different from themselves, and (f) help individuals explore ways to improve their effectiveness as senders or receivers of intercultural communication. At the end of a self-awareness training module, participants should better understand themselves and have a general sense of the areas in which they must improve to enhance the quality of their intercultural interactions. They will also begin to understand the constraints placed on them when engaging in intercultural interactions.

3.2. Perspective-Taking

The next step in the CCTE process is learning to take the other's perspective. Perspective-taking "encompass[es] the ability to perceive events the way others do and understand how other people's cultural values and assumptions affect their behavior. Perspective taking helps minimize the various kinds of cognitive and cultural bias[es] an intelligence [professional] may encounter during analysis" (Green Sands & Haines, 2013, para. 2). To take another person's perspective, people must relinquish control over their own cultural lens and suspend their own belief and value systems "in order to experience an alternate affective or cognitive state" (Abbe, Gulick, & Herman, 2007, p. 20). In the intelligence community, various techniques can help IPs assume alternative perspectives and challenge analytic assumptions, including "analysis of competing hypotheses"

(Heuer & Pherson, 2011) and "red teaming" (Green Sands & Haines, 2013; Mateski, n.d.). The goal is not to provide sophisticated stereotypical explanations that label cultures as falling within one category of a single cultural dimension (e.g., either individualistic or collectivistic), but to untangle the complex web of cultural syndromes that together create a unique cultural explanation within a particular situation and context (Osland, Bird, DeLano, & Jacob, 2000).

3.3. Surface, Process, and Deep Culture

Once IPs understand the complexities of cultural syndromes and individual profiles, they should learn how to identify artifacts or indicators that together could illuminate a cultural signature. For example, an IP might observe a paved highway that ends before it connects to another roadway. The IP must then explore what the highway symbolizes to the community and what its completion would mean to the people in the cultural setting. The IP might discover that the community views the incomplete road as a government ploy to show citizens that it is working toward fulfilling its promises, but at the same time needs the community to contribute to the completion of the road by supporting the re-election of the ruling party. Then the IP can begin to probe the layers of assumptions and underlying belief structures. Perhaps there is a generalized pattern of societal cynicism, exemplified by beliefs that people "will stop working hard after they secure a comfortable life" and "powerful people tend to exploit others" (Leung et al., p. 293). The underlying cultural values that lead to this generalized belief include hierarchy and mastery—principles that guide status and rules for dominating others. The IP must therefore peel back the surface layer of artifacts, the middle or process layer of meaning, and the deep core of assumptions to understand a culture.

3.4. Increasing Awareness of Communication Patterns

When observing dyadic interpersonal communication, IPs must first have a good model of the observable elements that identifies if and how the elements are connected: who communicates with whom; what, when, and how often they communicate; and what types of information are exchanged. IPs can apply social network analysis to gain this insight. A second fundamental aspect of communication concerns the role that each individual plays in the communication network (e.g., primarily a sender or a receiver). Role theory can help to illuminate this aspect. Finally, IPs must consider the detailed characteristics of the communication that occurs, including the semantics, grammar, syntax, and other nonverbal factors that together can yield a cultural signature. Together, these components form the basis for understanding relationship structures.

4. State-of-the-Art

This section describes state-of-the-art findings on perspective taking and communication patterns that inform CCTE designs.

Researchers have made numerous advances in the past decade that assist people to take on different cultural perspectives and improve understanding of relationship structures (Dien, Blok, & Glazer, 2011). These findings have yet to be incorporated in CCTE, as the protocols for perspective-taking and network analysis for identifying sociocultural signatures in relationships have not yet been tested outside of the laboratory. Below, we describe the latest findings on cultural priming as

a technique to support perspective taking, as well as network analysis, role theory, and relationship structures as tools for detecting and explaining identified artifacts. CCTE programs should incorporate findings from these research streams to the extent they are relevant to each agency's CCTE goals.

4.1. Perspective-Taking

One of the enabling objectives of CCTE is to prepare IPs to consider alternative perspectives. Current research from laboratory studies offers promising options for CCTE. Researchers have demonstrated methods that cue people to view artifacts through a cultural lens (e.g., individualism or collectivism) different from their own (e.g., Gardner, Gabriel, & Lee, 1999; Han, 2010; Oyserman & Lee, 2008a; Oyserman & Sorensen, 2009). Cultural priming studies (e.g., Gardner et al., 1999; Han, 2010; Oyserman & Lee, 2008b; Oyserman, Sorensen, Reber, & Chen, 2009) have provided behavioral evidence through application of psychological and neuroscientific methodology that people from North America and East Asia can be cued to think from different cultural perspectives, as evidenced by participants' change in endorsed values (Briley & Wyer, 2001, 2002; Gardner et al., 1999; Yang & Bond, 1980). Several studies have also examined the effects of priming on judgments about specific scenarios, such as acceptance of euthanasia or affirmative action (Kemmelmeier, 2003; Kemmelmeier, Wieczorkowska, Erb, & Burnstein, 2002).

4.2. Communication Patterns

Network Analysis. CCTE programs can employ a number of tools and techniques for *network analysis*: the process of modeling the relationships among a set of individuals, groups, or other entities based on data about them (Heuer & Pherson, 2011). Each entity is a *node* in the network; analysis identifies and quantifies the relationships, or *linkages*, between the nodes. These techniques are very useful for analysis of dyadic communications in that each data point represents a connection between two entities (e.g., observing the number of times Bill initiated a communication with George). By this measure, the strength of the link between Bill and George is a function of the total number of communications exchanged between them. It is critical, then, for IPs to be aware of the measurement unit used to determine associations (e.g., number of communications) when interpreting a network model.

One advantage of network analysis is that computational algorithms can directly quantify properties of the network as a whole (e.g., *degree of centralization*) or properties of individual entities within the network (e.g., *the centrality of Bill*). Quantities that refer to regular patterns of relationships among the entities are known as *structural variables* (Wasserman & Faust, 1994), because together they determine the shape of the network at a given time. As such, although these quantities provide IPs with the big picture, it is also imperative to distinguish between them and the quantities characterizing dyadic relationships between two entities.

Network analysis also has the advantage of allowing IPs to study the structure of the network at successive time points to understand the development of an organization (Kossinets & Watts, 2006). IPs can examine structure at a number of levels to understand interactions among different types of entities. Carley and Reminga (2004) observed that "organizations can be modeled and characterized as a set of interlocked networks connecting entities such as people, knowledge, resources, tasks, and groups" (p. 2).

With respect to understanding the culture of a given group of people, a *social network* is perhaps the primary model to use for inferring the nature of the relationship between any two individuals or groups and the function that relationship serves in the organization at large (Borgatti, Mehra, Brass, & Libianca, 2009; Heuer & Pherson, 2011). However, structured social relationships alone do not suffice to model culture (Carley & Reminga, 2004). The processes by which resources and information are managed (i.e., distributed and exchanged) among people living in a region, as well as the ways in which people interact with objects (e.g., tools, artifacts, icons) are distinguishing characteristics of culture as well. By layering network diagrams of these and other such factors upon social networks, richer pictures of the culture emerge, enabling IPs to study the effects of interactions among these different modalities on culture.

For example, IPs can augment their understanding of the relationship between Bill and George if their closeness in the network reflects not just the number of communications they exchange, but also the amount of time they are physically co-present with each other and the number of times they exchange money or goods. If Bill and George are known to communicate and be co-present frequently, but have few exchanges of money or goods, then it is not likely that the two men are business associates. One challenge for CCTE, then, is to improve IPs' abilities to quickly interpret the abstract network models in terms of the real-world sociocultural signatures associated with the modeled data.

Role Theory. One way for IPs to interpret sociocultural signatures associated with modeled data is to understand the role played by each entity in the social structure. Role theory states that within any given context, each person has a role that is influenced by expectations (from others) or the person's own interpretation of expectations about socially acceptable behaviors (Beehr & Glazer, 2005). In a role set analysis, members of an individual's role set include the focal person, who is typically the role receiver, and multiple role senders. *Role senders* (i.e., people who have a stake in the focal person's role) communicate expectations for appropriate behaviors to the *role receiver*. Examples of role senders include supervisors, peers, subordinates, family, and others who interact with the role receiver. The role receiver interprets role senders' communications (or lack of communications) and reacts to the perceived expectation.

As an example, members of a supervisor's role set include his/her own supervisor, subordinates, peers, family members, and fellow members of professional associations. Some subordinates might transmit the expectation of explicit instruction; in response, the supervisor provides them with detailed instructions. Other subordinates expect full autonomy, and the same supervisor responds by giving them only high-level directives without detailed instructions. If the relationship between sender and receiver is known, it is easier to correctly interpret messages between them on the basis of that relationship.

Relationship Structures. Once IPs have identified role senders and receivers, they must examine the structure of the relationship. According to Fiske (1992), dyadic relationships can be characterized as communal sharing, market pricing, equality matching, and/or authority ranking. Communal sharing refers to treating individuals within one's in-group as equivalent to oneself due to some shared similarity or set of similarities. Individuals in a community are all afforded the same rights, regardless of their contributions to the group. Authority ranking is defined by viewing

relationships on the basis of position or status in a hierarchy. Equality matching refers to maintaining the balance of favors and payments in a relationship and either eliminating or keeping track of any imbalances that arise. Market pricing refers to a utility and equity-based relationship that is determined through a subjective cost-benefit analysis of proportional contributions to the relationship.

These core relational models (RMs) are considered universal, but the ways in which they are expressed in different situations differ across cultures (Fiske, 1992). Moreover, an RM cues a variety of detailed prescriptions, propositions, precepts, and principles that might help explain individuals' thinking (Fiske, 2004). A thorough comprehension of how a given culture views relationships can help an IP better understand the motivations of role players and the rationale behind the dyadic interactions.

Summary. CCTE designs can incorporate each of the above approaches to understanding social systems. Indeed, the USG already uses some of the techniques reviewed, such as perspective taking and network analysis, to improve analytic tradecraft. However, increasing use of these techniques does not, by itself, lead to increasing cultural awareness; it simply enables identification of sociocultural signatures. CCTE should help motivate IPs to apply these techniques toward reaching cultural, rather than merely situational, interpretations of events or sociocultural signatures. We therefore propose that the USG further improve IP performance by using CCTE to help IPs apply the techniques to understanding particular cultures.

4.3. Cross-Cultural Training and Education

People in the United States tend to view training and education as the 'culturally appropriate' processes for developing work-related competencies, including competencies for international assignments (Fowler, 1994). Although cultural immersion programs, where a person embeds in a society for an extended period of time, can also be helpful, such programs tend to send people to one country only and can be quite costly. In this section, we address the state-of-the-art in CCTE, including several different types and modes of training that have proven useful, such as critical incidents, role-plays, and scenario-based training.

Since the 1990s, much research has been devoted to demonstrating the benefits of CCTE, including cost reduction, improved performance, and more effective decision making (Brugman, Reinhart, Feinberg, Glazer, Falk, & Castle, 2010; Brugman, Reinhart, Feinberg, Falk, & Castle, 2012). CCTE teaches people to engage in deeper analysis of surface observations. Knowledge and skills acquired from CCTE are important for creating cultural fluency and better understanding of others. These competencies give people tools to attend to the big picture, encourage cognitive flexibility, and reinforce a proclivity for asking searching questions.

Culture-Specific vs. Culture-General. Sometimes CCTE focuses on a specific culture to prepare people to work in or on a culture of interest. Although in the short term such training has benefits, it does not produce a great deal of transferrable knowledge and or skills that would apply to any culture of interest. Therefore, the USG should provide culture-general training and education that would give students the declarative and procedural knowledge, skills, abilities, and attitudes they need to understand and work in or on different cultures of interest. For example, someone who works in Russia and has received culture-specific training on Russia might work successful missions

there, but might fail if asked to work on Uganda without culture-specific preparation. With culture-general training and education, the learner builds cross-cultural competence and can more easily fulfill missions that call for shifts in cultural perspectives. Still, both are needed if we are to build confidence in our deep cultural understanding.

Training vs. Education. Another important consideration is that training has different goals than education. Culture-specific or general training might prepare people to identify artifacts and determine what is in the environment, whereas education provides tools for deeper explanation of how and why the observed artifacts were created. In this section we consider different modes and media that the USG could use in designing training or education.

Learning Modes. *Didactic learning* modes reinforce cognitive development through passive receipt of information, such as listening to lectures, or active seeking of information that can be found in library resources. Other methods for imparting information include briefings, reading materials, and cultural assimilators (in which learners are presented with decision-making scenarios for which they are then asked to choose a behavioral response option before receiving feedback on their choice). By contrast, *experiential learning* is an active mode of learning, where the student participates in the learning process by practicing behaviors and engaging in course-relevant content. It enables students to develop the capability of learning on their own. Example activities include field trips, role-plays, and simulations. See Figure 1 for additional modes of CCTE.

Mode of Learning		Culture-Specific	Culture-General
	Didactic	Lectures, briefings, films, books, cultural assimilators, critical incidents, case studies, language courses	Lectures, films, books, critical incidents, case studies, self-awareness exercises, videos
	Experiential	Role plays, case studies, assessment centers, simulations, field trips/studies, visual imagery, scenario-based training	International potluck, interviews of international sojourners, simulations, analyzing international films, multinational virtual or joint learning programs

Figure 1. Culture training and education.

Both didactic and experiential learning modes can reinforce students' knowledge and detection skills with regard to each of the four enabling objectives (self-awareness; perspective taking; surface, process, and deep culture; and communication patterns). Experiential activities often

impart methods for *knowing how*, whereas students learn the methods for *understanding why* through cognitive learning activities (e.g., lectures and readings).

Furthermore, learning content for each of these modes can range from highly specific to culture general. An example of a culture-specific didactic learning mode might be reading about the culture of the Druze, whereas a culture-general didactic learning mode might be reading about the role of religion in organizing societies.

Either didactic or experiential cross-cultural learning programs are better than no training at all, and are better than in-country training without guided learning (Goldstein & Smith, 1999; Korhonen, 2002; Sizoo, Serrie, & Shapero, 2007; Soeters & Recht, 2001), but neither is necessarily better than the other (Hammer & Martin, 1992; Harrison, 1992). Augmenting experiential CCTE with didactic CCTE aids learning (Harrison, 1992; McDaniel, McDaniel, & McDaniel, 1988).

Media for Training and Education. Program designers must also consider the media for delivering CCTE. The three basic media for delivering training and education are *face-to-face (F2F) instruction*, *web-based distance learning (DL)*, and *blended* or *hybrid learning*. The results of a controlled experiment by Gannon and Poon (1997) showed little difference in knowledge gain between hybrid (simulation game), F2F (lecture, discussion, group exercise), and DL (video-based training). However, MBA students who took part in the hybrid approach felt more satisfied and considered the experience more useful and relevant than students who took part in the other learning experiences. Note that each of these media supports both didactic and experiential learning modes. Below, we describe three commonly used CCTE techniques that support students' achievement of the enabling objectives. Instructors can employ these techniques with any teaching media.

***Critical Incidents*.** *Critical incidents* is a cognitive training tool in which learners must react to situations that mimic real-life critical behaviors and decision points (Fowler & Mumford, 1995). Through this tool, learners respond to descriptive situations in which an incident requiring cross-cultural adaptation occurred. When reviewing a critical incident, learners use their newfound understanding of culture and self-awareness to put themselves in the place of the incident's focal character. Through self-reflection and discourse, trainees discover their own implicit biases as they are guided to consider alternative cultural perspectives as a way of better understanding or appreciating the focal person's experience. A facilitator knowledgeable in the culture of interest encourages the trainees to discuss what they learned about themselves and their explanations of others' behaviors and attitudes, how one personally deals with a situation in comparison to others in the training session, and what cross-cultural skills became more visibly needed for the trainee (Dant, 1995). This activity provides an immediate, instructor-facilitated opportunity to utilize new knowledge and enables instructors to determine areas to emphasize further in training/education programs.

***Role-Plays*.** In *role-plays*, participants either take on a predetermined characteristic or observe people who are playing roles. Typically, the goal for engaging in role-play is to develop or improve interpersonal interactions in an intercultural setting; the role-plays assist in skill building (McCaffery, 1995). Although analysts rarely engage in interpersonal interactions in foreign cultures, role-play can nonetheless help IPs develop better self-awareness and perspective-taking skills,

improve their abilities to discovering deep and process cultural factors in observed behaviors, and help them to distinguish features of a particular dyadic communication interaction.

Scenario-Based Training. *Scenario-Based Training* (SBT) helps learners develop the skills needed for complex decision-making, problem solving, and adaptability. Although reading about the results from others' active engagement in an SBT can be useful for passive learning, active participation is much more educational. A well-crafted SBT has a curriculum developed around a particular scenario and provides trainees with information, demonstrations, and practice in real-world situations. Facilitators insert events into the scenario that form the basis for the learning objectives. The events, therefore, help students develop the skills to think of alternative ways of reaching decisions.

This technique differs from classroom lectures in that it uses real-world scenarios, provides opportunities for practice, and offers immediate feedback on process and results. Whereas listening to lectures is passive (see Moats, Chermack, & Dooley, 2008), participating in SBT is active and therefore has greater likelihood for transfer of learning to on-the-job performance.

Furthermore, Joung, Hesketh, and Neal (2006) found that training firefighters with scenarios depicting management errors and severe consequences (i.e., error-story training) yields better performance outcomes on simulated scenarios than training that walks trainees through incidents managed without errors. This suggests that people can learn from others' mistakes better than they can learn from others' successes. As such, SBT can prove more cost effective, safe, and successful at developing appropriate competencies, because it provides efficient methods to help personnel acquire and transfer complex knowledge, behaviors, and attitudes.

4.4. Summary

In this section, we outlined some findings from state-of-the-art research on culture, as well as modes and media for CCTE. An important point to make here is that we do not advocate any one particular mode or teaching medium for CCTE, because training must be tailored to the audience and need. We do, however, endorse cross-cultural (culture-general) training as a foundation for all DoD and USG personnel in order to strengthen cognitive flexibility, openness, and ability to engage in sociocultural analysis.

5. Transitioning Cross-Cultural Training and Education into Operations

CCTE can contribute to developing *capabilities to discover, distinguish, and locate operationally relevant sociocultural signatures* derived from sociocultural behavior data. Although not everyone has the opportunity to gain experience through international contacts, CCTE can help IPs acquire knowledge and skills in detecting cultural nuances. Most CCTE programs focus on preparing sojourners to interact with people in different cultures. However, in this type of CCTE, the goal is not necessarily to prepare students for physical interactions, but to enable them to detect cultural underpinnings in extracted excerpts of communications. The activities in which trainees engage during CCTE programs can also be applied to this type of task.

We suggest that designers of CCTE programs roll out the curriculum in stages, corresponding to the aspects discussed earlier. First, IPs would receive cultural awareness *training* in which they learn

about their own culture and how others view people from their culture. Once people become aware of their own cultural orientations, they should become better able to detect differences in others. Second, IPs would receive training in perspective taking that emphasizes understanding behaviors from the viewpoint of culturally different others. Instead of asserting only a person-focused explanation, IPs would evaluate the situation in which the behavior occurred and consider the degree to which that situation might account for the behavior. Moreover, IPs would learn not to focus too much on the most prominent small elements, or on only one area for discovery, because doing so might lead them to ignore opportunities for detecting cultural nuances. Third, IPs should practice their skills in evaluating surface, process, and deep culture, possibly via critical incidents and SBT techniques. Finally, IPs need to develop their skills at detecting relevant dyadic relationships and explaining how these relationships influence the observed artifacts and why those relationships evolved as they have. To that end, IPs would benefit from cognitive skills training that would improve general detection skills (e.g., attention, working memory, critical and divergent thinking).

5.1. Recommendations for Transitioning CCTE Activities to Operations

Scenario-Based Training. SBT appears to be one of the most cost-effective ways of implementing CCTE, but multiple factors influence the success of a particular SBT. These factors include the expertise of the trainer, the organization's reward systems, the climate for error management, the learning environment, task requirements, the student's ability to transfer learning to real life, individual motivation, formative and summative evaluation strategies, content of the training program (including method, strategy, and tools), student's real-work life experience (i.e., accumulated time on the job), and the student's intellect (Salas, Priest, Wilson, & Burke, 2006).

Developing an SBT is time consuming and costly upfront, but in the long run the benefits outweigh the costs, as the program can be used with all trainees. The upfront costs cover selecting and populating the relevant scenarios (e.g., pulling archival intelligence that might be relevant to the Boston Marathon bombers) from which designers can identify the competencies necessary for students to perform effectively on the job, as well as any deficiencies in performance that require correction. If the scenario targets the right deficiencies, designing and implementing SBTs that focus on the upgraded competencies becomes easier, as does evaluating the training's success. Furthermore, once core competencies have been established, trainers can generate corpora of scenarios and assessment instruments for each, and then store, modify, update, and reuse them. This would promote comparability of performance over time across agencies and training sessions.

Social Relational Mapping. We also suggest a new approach to training that draws from the theory of communication patterns (social network analysis, role theory, and relational models theory). The social relational mapping method borrows from the methodology of social network analysis, in which nodes and linkages between nodes are represented, as well as Relational Models Theory, which states that any two individuals or entities interact in ways that support patterned social behaviors. Learners in this type of training would become skilled at asking and answering deeper questions about the relationship dynamics (structural and functional) underlying the situations under consideration. For example, is the relationship hierarchical, egalitarian, self-serving, or other-serving? Do people see others as they see themselves (communal sharing)? Are there clear

demarcations between superiors and subordinates (authority ranking)? Are people in the social network studied of equal status to the focal person (equality matching) or are they viewed as tools for getting what the focal person needs (market pricing)?

As an example, IPs might detect that women in Pakistan have the legal right to vote, but in practice cannot go out to vote. This might appear to be a clear instance of equality matching vs. authority ranking, but the explanation for this violation of equality matching and adherence to authority ranking might lie in the value of honor. Therefore, we recommend documenting the described relationships between nodes (or role players) in order to strengthen the construction of the sociocultural context in which any given focal person is embedded. In so doing, IPs will become better able to (1) take on the perspective of the focal person, (2) explain why links with other nodes are not as salient or strong, and (3) consider ways to protect and defend within the constructed sociocultural context.

5.2. CCTE Learning Sequence

Drawing upon practices that trainers use with sojourners, such as training pre-departure and post-arrival, we also recommend that operational organizations use training as an introduction, and also provide continuous learning and reinforcement to sustain IPs' abilities to adopt different cultural perspectives. Ideally, this would occur by default in immersion experiences, but our recommendations apply in the cases where those opportunities are not available or cost effective.

As with pre-departure training, a goal is to establish learners' expectations about working with cultural materials. Such training would reduce students' anxieties, increase their confidence that they can detect relevant cultural information, and reassure them that all information observed is culture laden. Similar to post-arrival training, on-the-job reinforcement of culture studies would address real-time issues as experienced in the actual work setting. This is all the more important as IPs can become so immersed in their subject matter that they are sometimes unable to distinguish between their own cultural biases and those of the culture they are analyzing.

For this reason, we recommend a four-pronged approach to learning: listening, practicing, reviewing, and engaging. Listening refers to all the upfront learning, as well as ongoing learning that results from interacting with fellow IPs. Practicing also occurs during training, but in addition can occur through red teaming with others who share similar cultural cases. Reviewing includes reading layperson's materials (e.g., tour books, books about a society that can be found in the library or bookstore, and news journal articles), asking questions of cultural experts, and reminding oneself of one's own cultural biases. Finally, engaging refers to the habitual practice of preparing commentary and collateral evidence on all analytic tasks. It addresses the need to obtain critical feedback from other experts on a focal cultural group, as well as from people who are critical evaluators of detecting cultural nuances. As in software engineering, a checks and balances (or Quality Assurance) process must confirm that analytic products are appropriately framed in a sociocultural context.

Finally, it must be noted that one of the challenges in transitioning CCTE into operations is ensuring that those who conduct it are themselves experts. Trainers must have deep intercultural experience, a strong foundation in social psychological processes, and the ability to see big picture

influences. Moreover, IPs should work with people who are experienced with a cultural target to obtain guided critical feedback in their sociocultural analysis.

5.3. Evaluating Operational Utility

Empirical inquiry has just begun to explore the extent to which cross-cultural training has proven useful for IPs or military personnel deployed abroad. Criteria for performance measurement are still in development, and may not be available for a few more years. Even so, organizations have ways to determine the utility of CCTE programs. One indicator of CCTE success would be a noticeable increase in the depth or richness with which IPs interpret a situation. This measure would require a comparison of baseline analytic performance to performance after CCTE. Instructors might evaluate the utility of CCTE programs across multidisciplinary and multi-agency teams of IPs, including technology experts and social scientists.

Furthermore, instructors can develop evaluation forms for subject matter experts to use in evaluating IPs' reports prior to training and then again after have had a chance to revise their reports post-training. Evaluators would look for content changes that relate to cultural understanding, such as those found in collateral or commentary, indicative of more expert understanding of the culture. We would expect that IPs who receive cross-cultural training would provide more culturally informed and relevant explanations in their products than IPs who had not received the training.

Another measure of CCTE effectiveness is whether analytic reports more accurately characterize, explain, or forecast future events in a given situation. This is a difficult measure to derive, however, given that no one can be certain that sociocultural analysis was accurate until an event occurs and the analysis is found to have flaws. Airlines have learned to prevent accidents and incidents by studying data available from FAA logs, and therefore now take preparatory steps to enable flight crews to communicate with each other and tower control through training and education (McIntyre, 2000). Similarly, scholars of national culture must study factors omitted from earlier reports that, viewed through a sharp cultural lens, would have indicated cultural signatures alerting to imminent danger. Through this type of evaluation, CCTE designers can ensure inclusion of relevant cultural factors that would become required features of improved CCTE for IPs.

Ultimately, the return on investing in CCTE will take the form of increased security from foreign threats and smoother interactions with foreign national diplomats, but transitioning CCTE into operations requires policy makers to reinforce policy directives, such as Intelligence Community Directive 2.0.3, Analytic Standards. This directive encourages inclusion of collateral and commentary in reports.

We also strongly recommend that members of the analytic community work with people outside their own groups or agencies. The sharing of expertise between people from different groups and agencies can lead to insights and perspectives across disciplines—a process very much akin to detecting cultural signatures in the world at large.

6. Conclusion

In this chapter, we argued that the ability to detect those aspects of a situation central to defining the sociocultural context depends on the observer's deep knowledge of the cultures involved and what the artifacts mean in each of them. We proposed that an important step toward achieving this knowledge is for IPs to obtain CCTE that, over time, will help them become more sensitive to the relevant sociocultural signatures.

As we have shown, the key questions that must be answered in order to detect cultural patterns are "*how?*" and "*why?*"—not just "*what*?" CCTE enables IPs to develop awareness of the ways in which their own culture influences their thinking, become more adept at seeing events or artifacts from others' point of view, and more clearly understanding the multiple layers comprising every culture. We have also pointed out how network analysis and social radar can be useful tools for mapping potential factors that contribute to a social situation, and that training in social relational mapping can equip IPs to explain the observations made through these tools. Further, we recommended considering SBT as an especially cost-effective approach to improving people's sensitivity to culture cues. Given the findings of CCTE researchers, we appear to have good grounds for expecting that increased cross-cultural experience will help IPs provide contextual background that policy makers could use to forecast and mitigate potential threats and to facilitate peaceful operations.

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Section Three: Forecasting

Forecasting the sociocultural environment and behaviors

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> Capabilities are needed for tracking and forecasting change in entities and phenomena of interest along multiple dimensions (time, space, social networks, types of behavior, etc.) through persistent sensing and modeling of the environment. (Schmorrow, 2011, p. 43)

Flynn, Sisco and Ellis (2012) wrote "With a deeper understanding about populations, <we> will be able … to more accurately analyze how contemporary threats will likely impact populations and identify means for counteracting them when they are potentially harmful. But the process begins with a robust … capability before threats manifest themselves." This encapsulates a major challenge of HSCB forecasting. The chapters in this section describe the state-of-the-art capabilities available to meet some of these challenges, as well as emerging capabilities that are likely to be useful in the near future.

Data Processing

The chapter on data processing addresses issues related to representing a particular sociocultural system in a way that involves only data about an actual, ongoing situation that can be used to (1) reveal meaningful changes in the system over time and (2) inform models that can help users to anticipate those changes. These characteristics distinguish data processing issues for forecasting from those in the Understand capability area, in that both current and historical data can aid in forecasting sociocultural behavior. They also separate forecasting from the Detect capability, where it suffices for algorithms to find patterns in data without predicting future behavior. The chapter centers on selected aspects of data processing relevant to dynamics-based models and illustrates the discussion with applications relevant to the dynamics of political and insurgent networks.

Computational Modeling

The computational modeling chapter emphasizes that the nature and basis of models used across the various social science disciplines differ, and also differ from those of the physical models that underlie traditional military simulation. Computational sociocultural models require the ability to represent and manipulate imprecise perceptual and cognitive concepts. This chapter describes how computational sociocultural models can contribute to forecasting human behavior and sociocultural interactions, and account for natural vagueness of human thought and communication, along with the dynamics, complexity, uncertainty, variability and unpredictability of actions and behavior. It discusses 11 different types of computational sociocultural models chosen to cover a broad set of approaches, but those types by no means exhaust the options available. (Note that all the other chapters in this section also discuss dynamic models in their respective contexts.)

Visualization

The chapter on visualization examines forecasting, analysis, and visualization using the 'social radar' metaphor and standard questions of interest to analysts of complex systems. The author illustrates the concept by the example of the Virtual Strategic and Forecasting Tool (V-SAFT) developed by Lustick Consulting, which represents a stand-alone offshoot of work performed by the Worldwide Integrated Crisis Early Warning System team at Lockheed Martin Advanced Technology Laboratories. The discussion uses the state space of the future produced by V-SAFT as a target for queries designed to distinguish plausible and probable futures from those that are merely possible. It also covers how the tool can monitor change across regularly updated versions of that state space in order to generate indications and warnings, and can offer opportunities for what-if experiments to clarify the implications of different assessments of key variables in the real world.

Training

The training chapter describes the current state of the science and technology related to training in sociocultural forecasting, and identifies gaps that research must address to develop capabilities for application in operational settings. The chapter begins with an overview of forecasting in the sociocultural domain, with an emphasis on forecasting change in cultural behavior and social structure. It explores the relationship between sociocultural sensemaking and forecasting and presents a use case to illustrate the problem. The chapter then surveys the literature on training for forecasting, with an emphasis on probabilistic forecasting, and highlights special problems associated with forecasting in the sociocultural domain, along with their training implications. These include the nature and range of problems being predicted, from short-term political actions and events to long-term change in a population's cultural values, beliefs, and behaviors.

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9 Data processing for applications of dynamics-based models to forecasting[1]

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1. Introduction

The Forecast operational capability tracks and projects change along multiple dimensions in sociocultural entities and phenomena of interest. This chapter addresses issues related to representing a particular sociocultural system in a way that involves (a) only data available for an actual, ongoing situation that can be used to (b) reveal meaningful changes in the system over time and (c) implement models that can help users to anticipate those changes. These three elements distinguish data processing issues for forecasting from those in the Understand capability area, in which historical – not only current – data can aid in understanding sociocultural systems. They also separate forecasting from the "Detect" area, in which it suffices for algorithms to find patterns in data without predicting future behavior or supporting causal models of how the system evolves. This chapter centers on selected aspects of data processing relevant to dynamics-based models, i.e., models that posit causal mechanisms of system evolution, rather than purely statistical models, and illustrates the discussion with applications in the domain of political and insurgent network dynamics.

The first section of this chapter briefly describes dynamics-based modeling methodologies and presents a model of group decision making as an example that will help guide the subsequent discussion. Dynamics-based models involve an important distinction between variables and parameters and the second section of the chapter discusses the requirements and considerations involved in calculating their values. Calculating parameters is particularly difficult and the extent to which they can be determined influences whether the output of a model can be evaluated with respect to an actual time scale or only with respect to equilibrium outcomes.

The chapter then presents two examples of applications, both concerning leadership elites and their organizations. Research has largely overlooked the behavior of leaders and organizations amidst the surge of interest in social media, population sentiment, and big data, yet this type of data is particularly important in tracking and anticipating change on time scales of operational concern with regard to entities subject to operationally relevant levers of influence. These two examples, presented in the fourth and fifth sections, use different types of input data. The first involves the use of expert judgments in conjunction with the group decision-making model. The second involves the representation and modeling of insurgent network behavior and shows how

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the ideologies, policies, and relationships among insurgent groups can be constructed using rhetoric as data and tracked over time. For the insurgent network application, the chapter presents a stochastic model of insurgent cooperation at the tactical level and compares the model results with the network's evolution as observed in the data. Finally, the chapter provides a brief discussion of gaps in knowledge and future research directions related to data processing and forecasting, focusing on areas relevant to dynamics-based models and political application domains.

2. Dynamics-Based Models

In dynamics-based models, variables can evolve based on their present state and their interactions with other variables. Thus, a variable can be affected by self-feedback, as in an exponential growth or decay situation in which the rate of change of the variable is proportional to its value, and by feedback from other variables in the system, as in a predator-prey model where the rate at which the number of prey animals declines depends on the number of predators. Typically, these models posit causal mechanisms that underlie the forms of the feedbacks included. For example, in a model that treats the spread of a revolutionary ideology like the spread of an epidemic, the rate at which the number of people "infected" with the ideology increases is taken to be the product of the present number of already infected people and the number of people who are susceptible but not yet infected (Epstein, 1997). This assumes that each interaction between an infected and susceptible person has a certain chance of resulting in a new adherent to the ideology, as in person-to-person disease transmission.

This product interaction between variables is an example of a nonlinear interaction. Nonlinear models can accommodate complex behaviors such as abrupt, discontinuous changes in the nature of the system's behavior. Such sharp transitions are often of highest importance in sociocultural forecasting, e.g., will a localized uprising result in a mass revolution? Indeed, the epidemic model contains a critical threshold, called the reproduction rate, above which the epidemic or revolution will take off but below which it will fizzle out. Purely statistically-based approaches such as regressions are ill suited to forecasting sudden transitions in sociocultural contexts, which is one reason why this chapter focuses on dynamics-based models. In addition, statistically based models often provide little insight into how interventions into a situation will play out; therefore, they cannot be applied to analyzing courses of action for the purposes of the Mitigate capability area. However, regardless of whether one uses dynamics-based models or statistical methods, sociocultural forecasting remains a difficult task, largely due to the lack of appropriate empirical data.

There are various ways of implementing dynamics-based models, three of which are briefly mentioned here: differential equations, stochastic models, and agent-based models (for a more detailed description of various modeling methods, see chapter 10 on computational models in the Forecasting section of this book). Differential equations give mathematical expressions for the rates of change in a system of variables that can then be solved, computationally or analytically, to show the values of the variables over time. The equations evolve variables in continuous time (difference equations are the discrete-time analog). The epidemic model noted above is most

readily expressed and analyzed in differential equation form. The Lanchester model for combat dynamics is another differential equation that may be familiar to some readers due to its prevalence in the combat simulations used in operations research (Epstein, 1997). Differential equations are typically deterministic in that the future evolution of the variables is precisely determined by their initial values (although they can be adapted to accommodate stochastic forcings). A class of critical transitions in which the state of the system can change suddenly and discontinuously, known as "bifurcations," can occur in nonlinear differential equations; for example, old states become unstable and disallowed while new stable states emerge.

Unlike differential equations, stochastic models allow variables to evolve in a random rather than a deterministic manner. Also, these models typically represent temporal evolution discretely rather than continuously. Often the models assume a Markov process in which the probabilities of the various future states of the system depend only on its current state. In a stochastic simulation of the epidemic model of ideology diffusion, one could simulate all the individuals in a population, endow them with different characteristics, and allow infected individuals to meet and infect susceptible individuals with given probabilities. Stochastic models are often used in simulating processes that occur over networks, such as opinion change and cultural transmission, and in simulating network evolution itself, as in the model of insurgent cooperation presented below. Scale-free networks – characterized by power law distributions in which a relatively few nodes have a greatly disproportionate degree (number of ties) – can be generated by a stochastic "preferential attachment" model in which new nodes have a higher probability of linking to high-degree nodes than to low-degree ones (Newman, 2010). Stochastic models can exhibit critical transitions resulting in abrupt changes of state in the form of phase transitions at large population sizes.

At its most general, agent-based modeling involves the specification of interaction rules for a system of agents in a group or population. These rules can be deterministic or probabilistic and expressed in terms of mathematical formulas, similar to differential equations and stochastic models. However, agent-based modeling diverges most notably from these other modeling approaches when the rules are essentially algorithmic: specifically, agent behavior is governed by a relatively complex process that accounts for strategies, heuristic rules, experience from prior interactions, and learning. Consequently, agent-based models can simulate very rich behavior, although the downside for forecasting purposes is that they usually require more data to implement empirically and more computational resources to simulate the parameter space for assessing potential outcomes. Examples of applications of agent-based models to social systems in specific real-world cases include the modeling of social identity dynamics (Alcorn, Garces, & Hicken, 2012) and political party competition (Laver & Sergenti, 2012).

Group Decision Making Model

To provide a specific example of a dynamics-based model and a more concrete basis for the discussion of empirical implementation issues, we now consider a nonlinear model of group decision making – one that has been applied for forecasting purposes (Gabbay, 2007; 2013). The model captures the evolution of group member policy positions under the influence of group

discussion and their own ideological preferences. Although the model is formulated as a differential equation system, it is expressed here only in terms of qualitative rules to avoid becoming bogged down in mathematical detail. The rules are:

1. Each group member's current position is affected by two forces: the *self-bias force* and the *group influence force*.
2. The self-bias force is the tension that an individual feels when his current position is different from his *natural bias* position, which is determined by ideological and strategic preferences such as the relative importance placed upon military, diplomatic, economic, and political factors. The self-bias force:
   a) Acts in the direction of the natural bias.
   b) Has magnitude proportional to the difference between the individual's current position and natural bias.
   c) Increases in proportion to the individual's *commitment* to his natural bias.
3. The group influence force is the tension that an individual group member feels when his position is different from those of other group members.
   a) The total group influence force on an individual is the sum of the coupling forces resulting from his pairings with all the other group members.
   b) For a given pairing, the coupling force on an individual acts in the direction of the position of the other member of the pair.
   c) The magnitude of the coupling force increases approximately linearly for small position differences but weakens for differences greater than the individual's latitude of acceptance.
   d) The coupling force that member *j* exerts on member i is scaled by the *coupling strength*, which characterizes factors such as how often *j* communicates with *i* about the policy matter at hand, their relative status, *i*'s perception of *j*'s credibility or expertise, and the importance that *i* attaches to group influence.

At high disagreement levels (i.e., large differences in natural bias) the model displays nonlinear behaviors, including sharp transitions between qualitatively distinct outcomes as the coupling strength increases; asymmetric, majority rule outcomes resulting from symmetric conditions; the existence of multiple stable outcomes for the same parameters; and the greater facility of less dense networks to reach decisions and reduce discord. These behaviors are not present at low disagreement levels.

3. Variables and Parameters

All dynamics-based models are characterized by variables and parameters. Variables define the state of the system as it evolves in the model over time. In the model above, the policy positions of the individual group members are the state variables. Other examples of variables in sociocultural models include cultural norms, attitudes, popular support levels for government or insurgents, sizes of social movements, violence levels, and network ties among individuals or organizations. For forecasting applications, the state variables should be either: (1) indirectly related to the ultimate object of interest, in the sense that the application is intended to predict and measure an

aggregated function of the state variables; or (2) the objects of ultimate interest themselves, in that the application is intended to predict and measure the future values of the state variables. For the group decision-making model, the first case would apply if the researcher's ultimate goal were only to forecast the final policy decision of the group. This can be done by aggregating the final policy positions of the individual group members according to a suitable decision rule (e.g., leader choice, weighted averaging, consensus). The second case would apply if the researcher also wanted to predict which group members will support the policy and which ones will dissent, which can be determined from the distance between their final position and the final policy. Another example of aggregating variables, as in (1) above, is a model of insurgency in which the state variables are the attitudes of individual population members toward the government and toward the insurgents, but the application seeks to forecast only the overall levels of support.

Parameters are model quantities that characterize the system exogenously, i.e., they are not affected by the state variables. Parameters play a key role in dynamics-based models in determining how variables interact with each other and the environment. In the epidemic model of militant ideology spread, parameters determine the ease with which the ideology can spread between individuals and the rate at which infected individuals are removed by government repression or counterinfluence. Referring to the group decision-making model above, the natural bias, is used to set the initial positions of the members; the commitment scales the strength of the self-bias force for a given displacement of each member's policy position from her natural bias; a person's latitude of acceptance sets the range of policies surrounding her own position that she will entertain and serves as the source of the nonlinear interactions; and the coupling strength between individuals scales the impact of relational factors on how effective a person will be at swaying another person's position. For stochastic models, the parameters determine how the transition probabilities between states depend upon the state variables.

Modelers usually take parameters as constant, but can make them time-dependent as well. Given the complexity of sociocultural systems, variables often provide feedback to parameters, but as long as the time scale of that feedback is slow relative to the time scale at which variables evolve one can still consider the parameters as effectively exogenous. If that feedback occurs at a rate comparable to the change in the variables, however, then the modeler faces a coevolution problem and should redefine the "parameters" as state variables. The group decision-making model example assumes that the members' changing policy positions have no impact on the coupling network between group members. This is reasonable for a relatively short decision-making episode, but if the model were examining a long time scale—say years—then policy positions would probably affect relationships under the operation of the homophily principle: "birds of a feather flock together."

One of the primary difficulties – perhaps the greatest one – in forecasting sociocultural phenomena is that many of the concepts used in social science theory as well as in common discourse are not readily quantifiable. Power, ideologies, policies, attitudes, beliefs, grievances, trust, relationships, disagreements, utility, etc., do not come in standard units like watts, meters, or amperes. For instance, a social network matrix may use a single number to represent ties between individuals, but that does not capture the complexity of social relationships.

Forecast, therefore, occupies a thorny middle ground in the abstract-to-concrete data spectrum between the Understand and Detect capabilities. To help *understand* general decision-making phenomena, one can model policy spaces in the abstract, but one must assign actual policies to policy space coordinates in order to *forecast* whether a particular country's leaders may decide upon war in a given situation. For *detection*, on the other hand, very specific, concrete, and readily quantified data such as the frequency of conversations may suffice to identify central individuals or communities in, say, an email network. However, that is not equivalent to identifying the top leaders who make strategic decisions in times of crisis and the relationships of authority and influence between them. Consequently, a key challenge in forecasting is to construct meaningful variables and parameters from relatively specific, more quantifiable, lower level data that can be reasonably mapped onto more abstract, higher order theoretical concepts.

This construction of conceptually broader variables and parameters is necessary not simply to connect with social science theory but also to reduce the dimensionality of the space of variables that must be predicted. Considering the group decision-making context, a group member's natural bias policy may be a function of her beliefs about the facts, the relative importance that she accords to the different components of the problem – military, diplomatic, economic, domestic political – and how she evaluates the policy options for each of those components. Although an analyst may be able to assess those factors for each group member, no model can be expected to predict the changes in each of those factors due to group interactions. It is therefore necessary to reduce the dimensionality of the space of the state variables by, for instance, combining the above factors to represent policy positions in a one or two-dimensional space. The subsections on analyst input and insurgent rhetoric present examples of ways to construct ideology and policies from lower level data.

Variables and some kinds of parameters can be calculated by applying the defining formula or algorithm to data representing a single time instant or interval independently of other times or other variables. However, feedback parameters in particular, which necessarily involve rates of change over time or the strength of interaction among variables, cannot truly be calculated solely on the basis of a predefined formula or algorithm that operates on data representing only one time. Ideally, one would measure the behavior of the state variables over time and then fit the parameters to the data, similar to the way parameters are measured experimentally in physical systems. This is also analogous to statistically based pattern recognition and forecasting methods in which an in-sample is used to fit parameters that are then applied to out-sample data. Such a fitting procedure can be used to determine parameters in sociocultural systems, but typically is difficult to carry out to much precision due to the lack of sufficient data points over time and the relatively large amount of noise in the data, among other factors. This is particularly true of the conflict-ridden and chaotic regions of interest to the U.S. military. When fitting parameters to existing data is not an option, then modelers can choose parameter values in an a priori manner based on considerations of what constitutes reasonable values or ranges. Simulations can then sweep over a patch of parameter space in order to determine the sensitivity of the outcomes to changes in the parameters. Laver and Sergenti (2012) offer a thorough and candid discussion of the issues involved in parameter calculation for an agent-based model of political party competition.

4. Forecasting Modes

Dynamics-based models can be applied for forecasting purposes in a variety of modes. The modes available for a given application depend on the nature of the data. One mode involves predicting, in a probabilistic way, the evolution of variables that can change in a more-or-less continuous fashion over time: for instance, the levels of popular support for an opposition movement among different segments of the population. This would correspond to true forecasting in that one assigns time-dependent probabilities of the various possible states of the system, as is done in weather forecasting. However, as discussed above, this remains an ambitious goal for most models of sociocultural dynamics due to the limitations in measuring variables and parameters (as well as model uncertainty itself, a topic not considered in this chapter). Although it would be technically possible to develop simulation software that makes explicitly probabilistic forecasts, doing so could well be counterproductive in the absence of accurate and precise estimates of model variables and parameters. Otherwise, end users, accustomed to reliable weather forecasts, could be lulled into a false sense of confidence by the simulation's provision of numerical probabilities and, consequently, might be greatly disappointed by the inevitable large mismatch between the forecasts and reality.

A looser mode of forecasting can be applied to key events, such as conflicts, decisions, and alliance composition, which can be treated as one-off occurrences. In these instances, one relaxes the requirement that the model make forecasts over time and simply assumes that the time window is sufficiently long to allow the system to reach equilibrium. In the group decision-making model, the time scales that enter into the commitment and coupling scale parameters are not usually known, which precludes such a model from being used to forecast the evolution of the group members' policy positions in real units of time. However, the equilibrium positions themselves do not depend on the time scales, and so the model can still be used to predict the final decision and its supporters and dissenters, on the assumption that the debate persists until equilibrium. This equilibrium approach significantly eases data demands; many dynamics-based models use this mode in practice.

Sensitivity analyses in which simulations cover a region in the parameter space can also be employed for forecasting purposes. If the outcome does not vary significantly as parameters sweep over a range of reasonable or likely values, then the model user can conclude that the outcome is highly probable. Alternatively, the simulations may reveal a range of possible outcomes. These may include potential outcomes (e.g., alliance configurations) not anticipated prior to the simulation. Sensitivity analysis may also reveal that the outcome can change dramatically with only a small shift in parameter values, as would be consistent with a bifurcation or phase transition.

As an illustration, consider a group decision-making model in which all group members are connected with the same coupling strengths and have initial opinions (natural biases) symmetrically distributed around zero. More specifically, consider a three-person group in which a centrist is bracketed by two equidistant extremists. Standard intuition would anticipate either a deadlock or various shades of compromise around the centrist position, consistent with final states that are symmetric about the middle, as shown in Figure 1 (a) and (b) for deadlock and compromise respectively. However, at sufficiently high levels of initial disagreement, another outcome can result in which the centrist swings toward one of the extremes (depending on random

perturbations), corresponding to a majority rule situation favoring one side of the policy axis. In this case the system reaches an asymmetric final state as observed in Figure 1(c) (Gabbay & Das, 2014). Even a small change in coupling strength can produce a transition to the majority rule outcome zone from either the deadlock or compromise zones. If the simulation of a leadership group showed such behavior, analysts could be prepared for an extreme decision rather than deadlock or compromise.

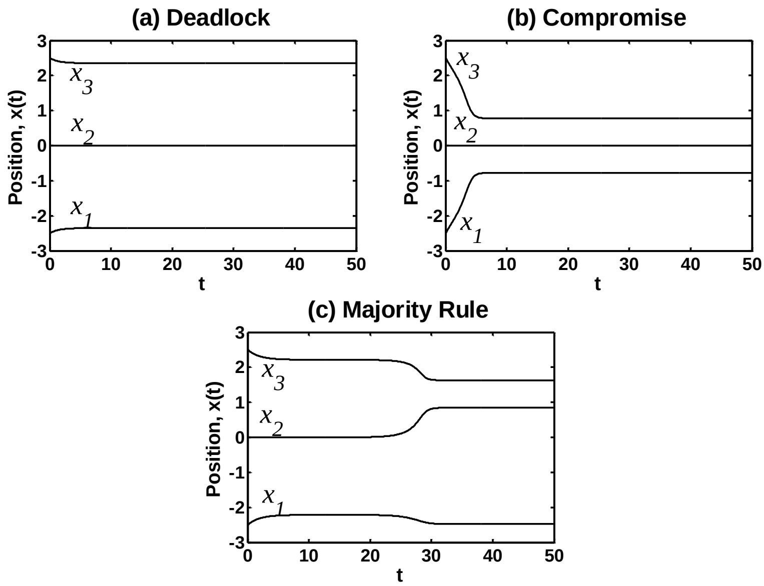

Figure 1. Group decision-making simulation of member positions over time in triad network (chain topology) with symmetric coupling strengths and natural bias distributions: (a) symmetric deadlock outcome at low coupling strengths; (b) symmetric compromise outcome at high coupling strengths; and (c) asymmetric majority rule outcome at intermediate coupling strengths. Adapted with permission from Gabbay & Das (2014).

Finally, dynamics-based models can be used to conduct scenario analyses to forecast the effects of specific hypothesized contingencies or conditions. These analyses can be implemented by particular variable or parameter settings that represent exogenous impacts on the system due to events or actions outside the dynamics of the model. For example, in a group decision-making situation, one can simulate the effect upon the policy outcome of a rupture in the relationship between two group members due to a personal dispute unrelated to the policy context. This could be done by nulling or severely attenuating their mutual coupling strengths, possibly in combination with other parameter changes.

5. Analyst Input for Group Decision Making

The two principal sources of data for calculating the “soft” variables and parameters (opinions, beliefs, ideologies, norms, social identities, etc.) needed as model input are analyst (subject matter expert) judgments and content analysis. Currently, analyst-based input represents the prevalent

form of input (e.g., Alcorn et al., 2012; Feder, 2002; Gabbay, 2013), but the use of content analysis-based input is growing, especially given recent advances in automated text analysis. This section briefly discusses the use of analyst input in conjunction with the group decision-making model described above. The next section describes an application of content analysis using rhetoric as input data for the context of insurgent network dynamics.

Figure 2 shows the processing chain to implement the model for specific leadership groups using analyst judgment for input. The modeler obtains this input from a survey given to one or, preferably, many analysts. A composite analyst can be formed by averaging the survey responses of the individual analysts. The aggregation of individual surveys allows analyst judgments to be synthesized independently of each other. This minimizes the chance that social pressure will alter individual judgment, as can happen if the modeler elicits inputs in an oral discussion with a group of analysts – a common practice in other models of group decision-making used within the national security community (Bueno de Mesquita, 2009). Note that results can be generated on the basis of individual surveys as well. This permits comparison of the results obtained from individual analysts with the composite analyst and with each other, thereby providing a way of stimulating debate about differences between analyst viewpoints.

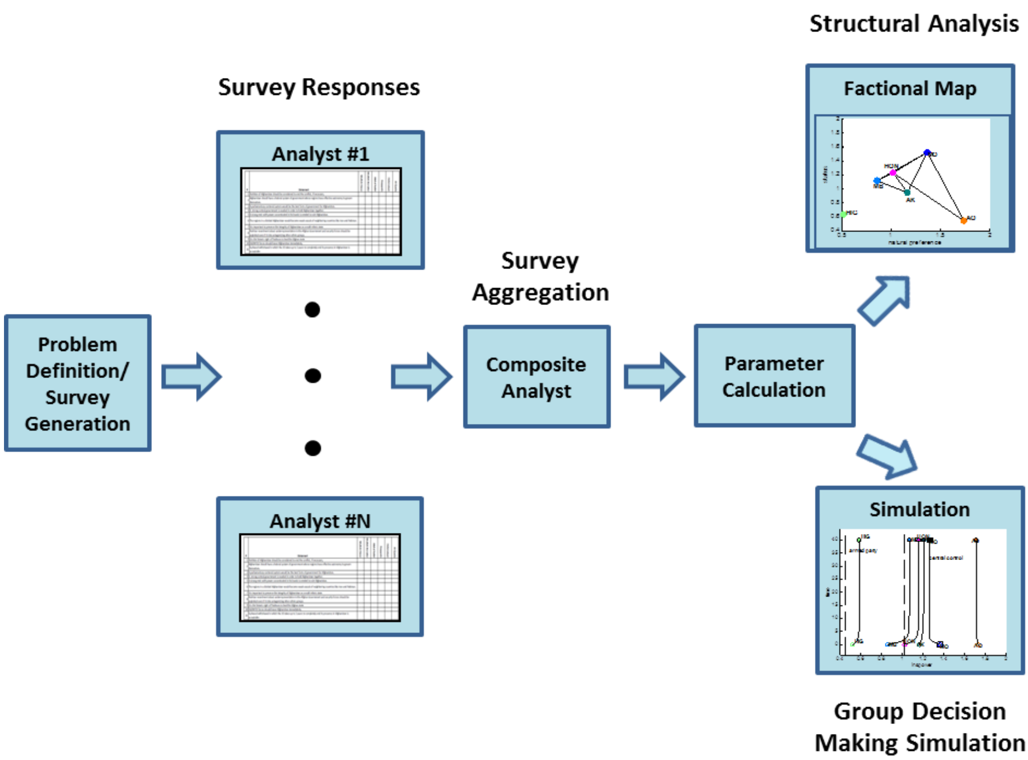

Figure 2. Overview of analyst input-based implementation of group decision-making model. Adapted with permission from Gabbay (2013). Copyright held by the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering.

Another innovation in this implementation methodology is the use of an attitude scaling technique to assess member ideological and policy positions. The natural bias, which is typically taken as the initial position of a group member, is constructed on the basis of a series of attitude statements for which the analyst rates the level of agreement or disagreement as if she were the group member in question, as shown in Table 1. This enables assessment of several different facets of the policy problem that can then be aggregated to calculate the natural bias. Also, modelers can probe the deeper structure of the policy space by using matrix decomposition methods such as principal component analysis. This approach elicits analysts' expertise on group member policy preferences without demanding that they directly perform the abstraction needed to create a policy axis or space itself — a task that the modeler accomplishes instead.

Table 1. *Sample attitude statements assessing ideological and policy preferences from an analyst survey on Afghan government elites. Analysts are asked to rate member attitudes on a five-point scale ranging from "strongly disagree" to "strongly agree"*

#	**Statement**	**Karzai**	**Fahim**	**Khalili**	**Rabbani**	**Dostum**	**Nur**
1	Partition of Afghanistan should be considered to end the conflict, if necessary.						
2	Afghanistan should have a federal system of government where regions have effective autonomy to govern themselves.						
3	Karzai's efforts to concentrate power in the presidency show that the Afghan Constitution should be changed to institute a parliamentary -centered system of government.						
4	A strong central government is needed in order to hold Afghanistan together.						
5	A strong leader with power concentrated in his hands is needed to rule Afghanistan.						
6	The regions in a divided Afghanistan would become weak vassals of neighboring countries like Iran and Pakistan.						
7	It is important to preserve the integrity of Afghanistan as a multi-ethnic state.						
8	It is the historic right of Pashtuns to lead the Afghan state.						

6. Rhetoric Input for Insurgent Network Dynamics

This section presents an application using input derived from content analysis – both automated and manual – in which the data source is Iraqi insurgent rhetoric. It describes methods for quantifying insurgent ideology, targeting policy, and cooperative relationships. Those three elements roughly correspond to insurgent ends, means, and allies respectively: critical components of their strategic behavior and decision making. These elements can be used to track insurgent behavior over time and as inputs in models for forecasting insurgent dynamics. A model of insurgent tactical cooperation is presented at the end of this section as an example of how such data can be used for simulating insurgent network evolution.

The modelers collected data for the 18 Iraqi Sunni insurgent groups listed in Table 2, spanning the time from mid-2003 through mid-2009. This time span is divided into three periods: (1) Period 1, August 2003 – July 2005; (2) Period 2, August 2005 – July 2007; and (3) Period 3, August 2007 – July 2009. The data set consists of roughly 2,000 translated insurgent statements from jihadist websites and interviews of insurgent group officials in print and broadcast media as provided by the U.S. government's Open Source Center.

Table 2. *Sunni insurgent groups in Iraq used in content analysis of insurgent rhetoric*

Group	**Symbol**	**Overall Classification**	**Islamist Ideology**	**Time Periods**
Al-Qaida in Iraq	AQI	Jihadist Salafist	Salafist	1,2,3
Ansar al-Sunnah Army (Ansar al-Islam: post-Dec. 2007)	ASA	Jihadist Salafist	Salafist	1,2,3
Islamic Army in Iraq	IAI	Nationalist	Salafist	1,2,3
Mujahidin Army	MA	Nationalist	Salafist	1,2,3
1920 Revolution Brigades	1920RB	Nationalist	Unspecified	1,2,3
Islamic Front for Iraqi Resistance	JAMI	Nationalist	Muslim Brotherhood	1,2,3
Rashidin Army	RA	Nationalist	Unspecified	1,2,3
HAMAS-Iraq	HAMI	Nationalist	Muslim Brotherhood	3
Fatihin Army	FA	Nationalist	Salafist	2,3
Iraqi Jihadist Leagues	IJL	Jihadist Salafist	Salafist	2,3
Shield of Islam Brigade	SIB	Jihadist Salafist	Salafist	2,3
Ansar al-Sunnah Shariah Commission	ASA-SH	Nationalist	Salafist	3
Just Punishment Brigades	JPB	Jihadist Salafist	Salafist	2,3 (part)
Abu Bakr al-Siddiq Salafi Army	ABSSA	Jihadist Salafist	Salafist	2,3
Islamic Jihad Brigades	ISJIBR	Jihadist Salafist	Salafist	1,2
Victorious Sect Army	VSA	Jihadist Salafist	Salafist	1,2
Saad Bin Abi Waqqas Brigades	SBAW	Jihadist Salafist	Salafist	2,3
Army of Naqshabandi Order	NAQSH	Nationalist (Baathist)	Sufi	2,3

Ideology

Ideology is quantified by the concept of a *conflict frame*. The conflict frame of a political actor, such as an insurgent group or government leaders, is defined on the basis of the set of out-group parties

perceived as current or potential enemies and in-group parties perceived as allies or as a base of support (Gabbay & Thirkill-Mackelprang, 2011). This definition stems from social identity theory and its implications for political rhetoric. *Conflict parties* consist of broad groups such as the incumbent government, ethnic or religious groups and their leadership classes, and foreign states. The mathematical formalism for conflict frames relies on the frequency with which specified marker terms appear in actor rhetoric and their in/out-group valences. Figure 3 is a conceptual diagram of the elements involved in the conflict frame calculation procedure. Sample marker terms and associated in- and out-groups are given in Table 3.

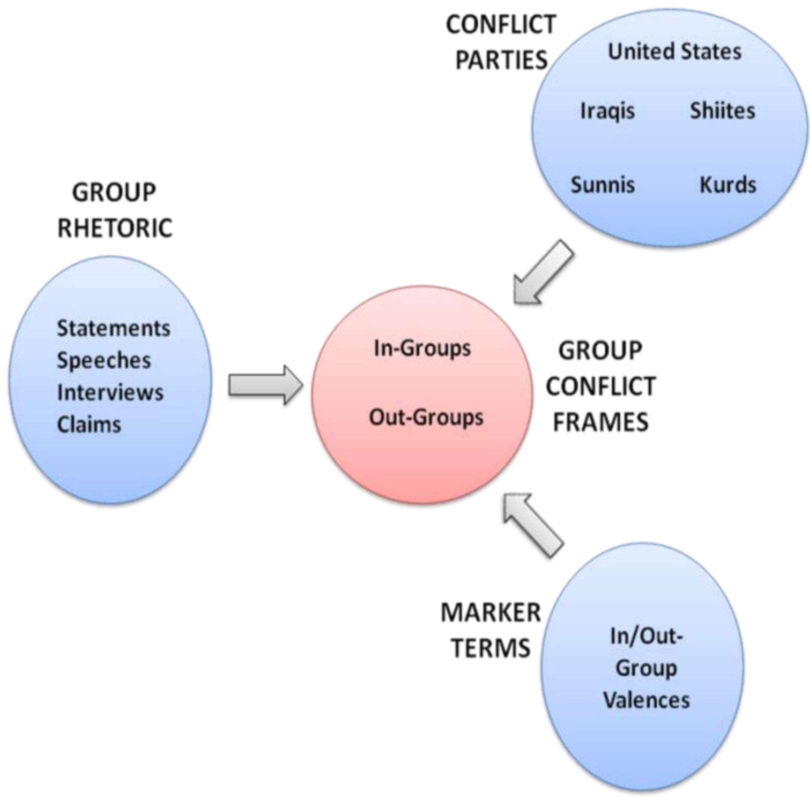

Figure 3. Conceptual diagram of conflict frame method of quantifying ideology.

Table 3. *Examples of marker terms and associated in-groups and out-groups for Iraqi insurgents*

Marker Term	**In-Groups**	**Out-Groups**
agent government		Iraqi Government
apostate government	Sunni Civil Society	Iraqi Government
companions of the prophet	Sunni Civil Society	
cross worshippers	Sunni Civil Society	United States
Iraqis	Iraqi Civil Society	
Iranian occupation	Sunni Civil Society	Iraqi Government, Shiite Political Parties
occupier		United States
rejectionist	Sunni Civil Society	Shiite Civil Society
rescue council		Sunni militias (Awakening Councils)

Each marker term is assigned a valence for all the conflict parties to which it refers: positive (+1) for in-groups, negative (–1) for out-groups, and zero for neutral references. A conflict party's *salience* to the actor is essentially the frequency with which marker terms referring to that party appear in the actor's rhetoric, regardless of valence. The actor's *attitude* toward the party is related to the relative frequency of positive and negative references to it. The attitude weighted by the salience represents the actor's *orientation* toward the party. An actor can have a highly negative attitude toward a conflict party but a low orientation value if the actor seldom refers to the party, which hence has low salience. The collection of orientation values for all the conflict parties forms the conflict frame of the insurgent group.

This procedure is automated following the construction of the initial dictionary and valence matrix and therefore can be updated in near-real time to track ideological shifts and divisions within the actor ensemble. An actor's conflict frame vector, composed of the actor's orientations toward the conflict parties, is the primary output of the algorithm. Another way of analyzing the data, however, is by considering certain master frames, which can be given intuitive interpretations. A master frame consists of a specified subset of out-groups and in-groups. The extent to which an actor espouses a given master frame can be quantitatively gauged by how closely its conflict frame aligns with the master frame – mathematically via the inner product of the corresponding vectors. Two master frames dominate for the Iraqi insurgents: (a) the resistance frame that pits Iraqis as in-group against the United States as out-group and (b) the sectarian frame that pits Sunnis as in-group against Shiites as out-group.

Figure 4 shows the conflict frames for the Iraqi insurgent groups over the three time periods.[2] The Jihadist groups—particularly the two major ones, Al Qaida in Iraq (AQI) and Ansar al-Sunnah—tend to fall on the high end of the sectarian frame and the low end of the resistance frame. The Nationalists, especially "pure" Nationalist groups such as the 1920 Revolution Brigades, JAMI, and the Rashidin Army, have lower sectarian frame values and high resistance values. However, it is important to note that the figures show a spectrum rather than two widely disjoint clusters of Jihadists and Nationalists, as would be implied by such a binary analytical classification. This spectrum quality and the locations of individual groups in the master frame coordinate space have meaningful implications for cooperative behavior among insurgent groups. The first two Nationalist alliances to nucleate comprised neighbors in the Period 2 master frame space: (1) the Jihad and Reform Front consisting of IAI, MA, FA, and ASA-SH; and (2) the Jihad and Change Front consisting of 1920RB and RA. This suggests that the conflict frame construct can provide meaningful and predictive input to models of insurgent alliance formation.

[2]The groups ABSSA and ISJIBR are not included (documents were not preprocessed to remove extraneous text).

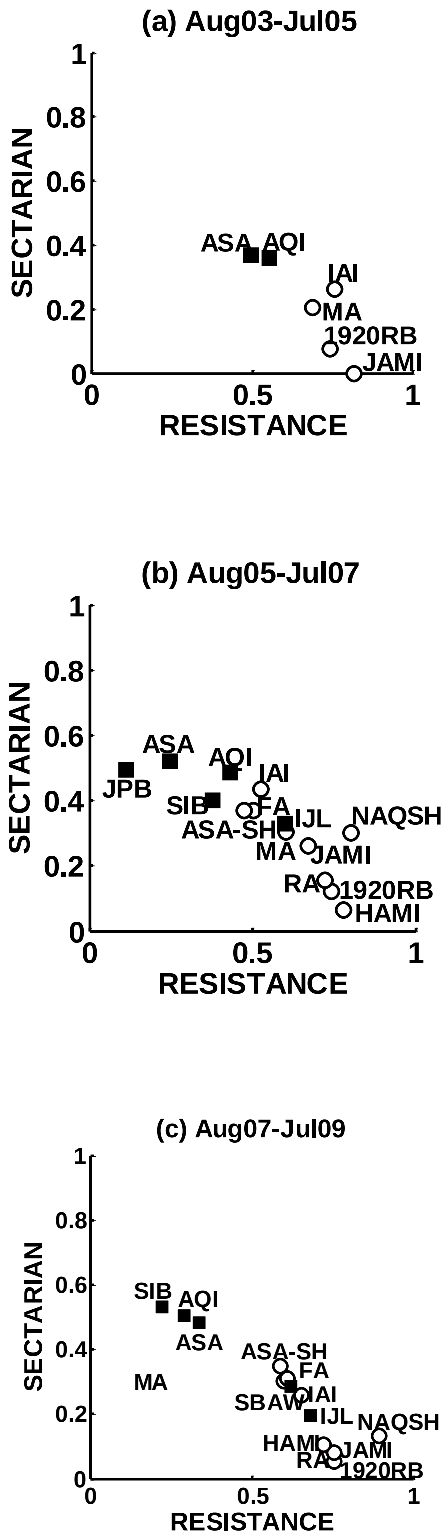

*Figure 4***.** Master frames for Iraqi insurgent groups: (a) Aug03–Jul05; (b) Aug05–Jul07; (c) Aug07–Jul09. Jihadists in black squares, Nationalists in white circles.

Tracking changes is one of the objectives of the Forecast area and the time-dependent behavior of the conflict frames can be tracked for either individual groups (as in Figure 4) or the whole ensemble. For example, in tracking changes in the balance between the two master frames for whole ensemble of groups, Figure 5(a) shows that the sectarian frame component increases relative to the resistance frame from the first to the second period, even among the Nationalists, and then wanes again in the third. This tracks the transition into a Sunni-Shiite civil war during 2006 and 2007 and the subsequent decline in sectarian violence. Ideological dissension within the insurgency can be tracked by looking at the frame deviation: i.e., how spread out the groups are in the space of master frames. Figure 5(b) shows the frame deviation in the resistance-sectarian master frame space. The deviation starts out low during the first period but increases and plateaus for the second and third periods. This corresponds to the character of factional relations within the insurgency. Early on, the groups were relatively united, but the transition to a sectarian civil war was a key factor in producing a rift between the Jihadist and Nationalist wings of the insurgency, eventually leading to the formation of the anti-AQI Awakening Councils and open fighting between Nationalist groups and AQI.

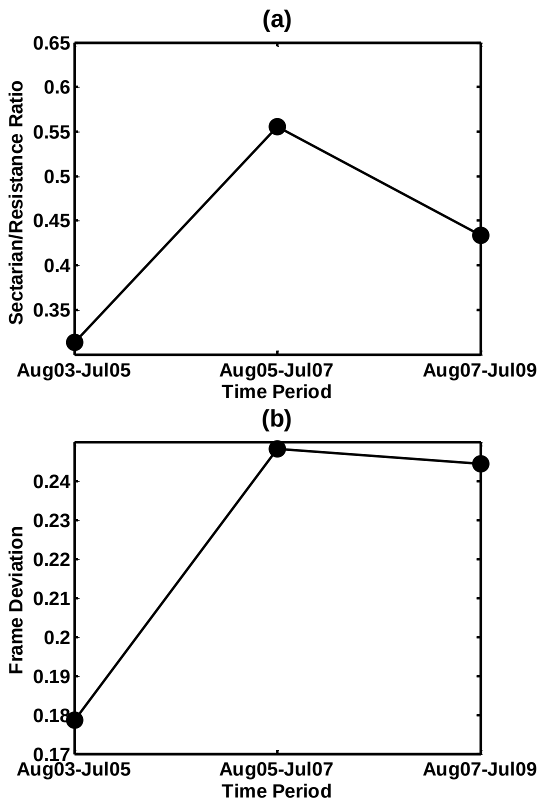

Figure 5. Temporal tracking measures for Iraqi insurgent ideology: (a) Ratio of mean sectarian frame value to mean resistance frame value; (b) Standard deviation in group two-dimensional frame positions from mean position of sectarian and resistance frames.

Targeting Policy

To construct the targeting policy variable, the portfolio of target classes—U.S. troops, Iraqi security forces, Shiite militias, government officials, civilians, etc.—claimed by different insurgent groups is considered (Gabbay & Thirkill-Mackelprang, 2011). The targeting policy scores each insurgent group by the average legitimacy of its target class portfolio, where the "legitimacy" of each target class is the acceptability of attacking it as determined by the prevalence, within the set of insurgent groups, of claims and statements supporting targeting the class vs. condemnations of doing so. A high targeting policy corresponds to a more discriminate or selective use of violence, while a low one indicates more expansive and controversial targeting practices. Implicit in this construction is that distance along the targeting policy axis is related to the extent of disagreement. This reflects that disagreement over the legitimacy of different types of targets has often been the primary source of dissension within Islamist insurgencies (Hafez, 2003).

Figure 6 shows insurgent group targeting policies over the second and third time periods. The groups are arranged along the vertical axis in ascending targeting policy order so that groups at the bottom have lower targeting policies. The figure shows that the Jihadists tend to have lower targeting policies and Nationalists higher ones. However, similar to conflict frames, this reflects a spectrum rather than a binary distribution. Like conflict frames, targeting policy can also be used to track dissension among insurgent factions; the standard deviation of the targeting policy increases over time in tandem with the actual rise in dissension within the insurgency (Gabbay & Thirkill-Mackelprang, 2011).

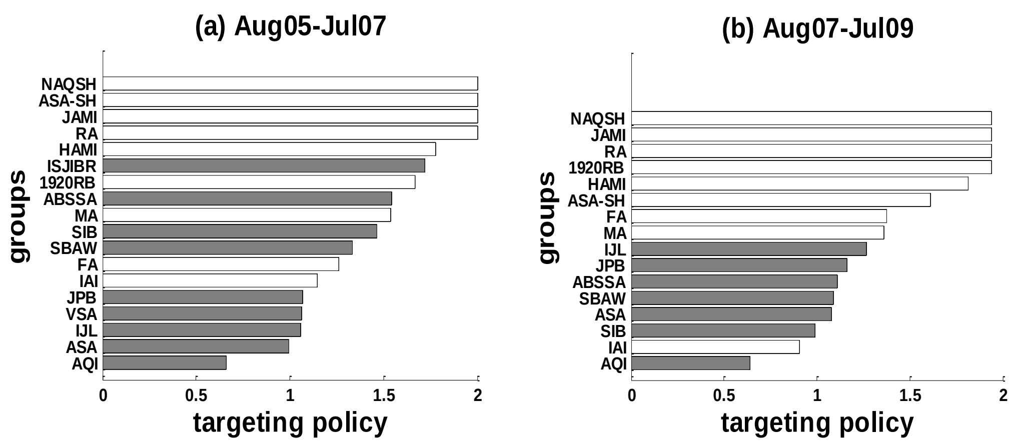

Figure 6. Targeting policies for Iraqi insurgent groups: (a) Aug05 – Jul07; (b) Aug07 – Jul09. Jihadists in gray, Nationalists in white.

Cooperative Networks

The rhetoric-based methodology constructs networks representing cooperative relationships among insurgents at both the leadership and rank-and-file levels. Leadership relationships among groups are gauged by the number of joint communiqués they issue. A joint communiqué is a statement signed by two or more groups, indicating the presence of communication and some

level of agreement among the leadership of the groups issuing it. Furthermore, it demonstrates a willingness of the groups involved to be publicly associated with each other. At the rank-and-file level, the method uses the number of joint operations between groups. Typically, only one of the participants makes a claim of joint operations. Such operations indicate tactical coordination among insurgent groups, although presumably a group's leadership would have to approve the public disclosure of such cooperation. Figure 77 (a) shows the joint operations network for the third time period; Figure 77 (b) shows the simulated version, which is discussed presently.

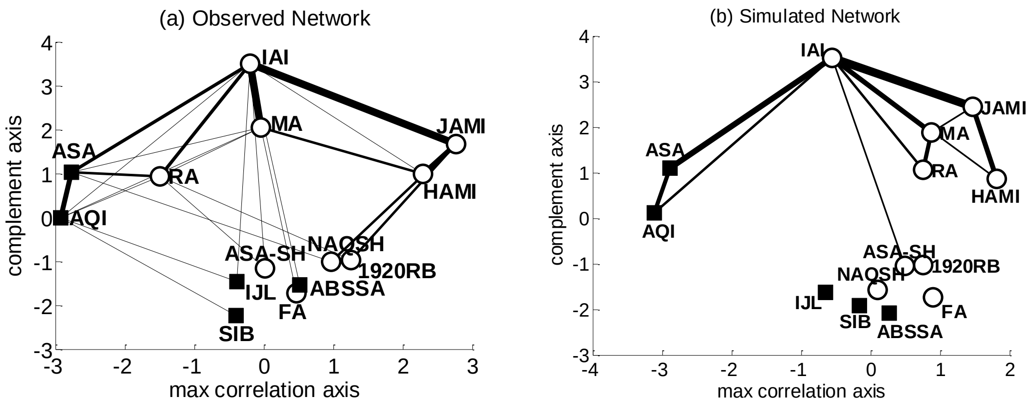

Figure 7. Joint operations networks for Aug07 – Jul09: (a) observed; (b) simulated. Jihadists in black squares, Nationalists in white circles.

Application to Modeling Insurgent Tactical Cooperation

The elements of the above representation can serve as input data for a stochastic model of insurgent tactical cooperation (Gabbay & Thirkill-Mackelprang, 2010). The model variables are the numbers of joint operations between insurgent group pairs, whereas targeting policy and the leadership network ties are taken as fixed parameters. The model assumes that each insurgent group has a number of foot soldier field units that may cooperate with the units of other groups. The model describes the probability that some unit from group *i* will conduct a joint operation with some unit from group *j*. It assumes that the joint operation process depends on the group sizes, the number of prior joint operations between units of *i* and *j*, their tendency to interact with similar other groups, their targeting policies, and the presence or absence of leadership relationships. Figure 8 shows a diagram of the process.

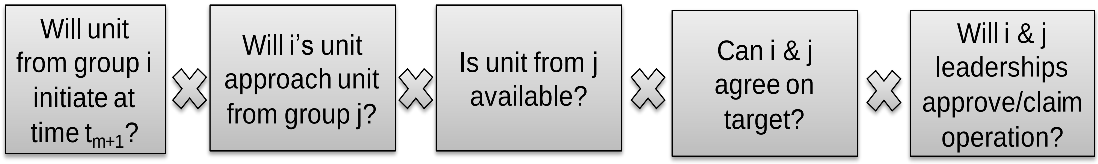

Figure 8. Simulated process for evolution of a joint operations network.

An important feature of this model is its positing of roles for both horizontal interaction in which foot soldier units can, on their own initiative, cooperate with units from other groups and a hierarchical process through which group leaderships can decide whether or not to let such operations go forward and/or claim responsibility for them if they occurred. This horizontal and hierarchical blending manifests the hybrid nature of insurgent groups that mix formal and informal organizational structures.

Figure 7 displays a comparison of the observed and simulated networks for the third time period. The simulated network represents the average over 500 simulation runs. The simulation used the state of the joint operations network in the previous period to represent the initial conditions, but used the targeting policies and leadership network of the third period to better assess the tactical cooperation model itself. Model parameter values (other than the fixed targeting policies and leadership networks) were chosen based on intuitively reasonable estimates and set to be the same for the simulations of the second and third period networks; some variation of parameters was conducted but an extensive search of the parameter space to optimize results was not performed. The visualizations show good agreement in the placement of the insurgent groups; only MA and RA are significantly out of place in the simulation (readers should ignore the links in the simulation plot as they have been thresholded to unclutter the graphic). For forecasting purposes, analysts could employ such a model to predict changes in patterns of insurgent cooperation under different scenarios, such as increased dissension over targeting practices.

7. Future Research Directions

This section identifies some current shortcomings in existing capabilities for data processing in the Forecast capability area and suggests future research directions. By necessity, the discussion is selective and emphasizes areas related to the types of application domains presented in this chapter. It also stresses the need to develop data appropriate for dynamics-based models, advocates more dedicated efforts to collect and process data on elites and their organizations, and suggests the development of multi-level network representations as one avenue for structuring this data.

Data processing is a critical enabling capability in the application of dynamics-based models for forecasting purposes. Better data will naturally lead to better models. While this is true of both statistical and dynamics-based models, the latter ultimately hold more promise. Statistical methods are powerful because they often can be applied to data in a context-independent way, but they have serious limitations when applied to the contexts of particular concern to national security

analysts, planners, and policy makers—situations often marked by crisis, conflict, and chaos. For example, regression models can endeavor to forecast future violence levels in a conflict using only a time series of past violence levels without any need to know about the power balance, constraints, and internal dynamics of the warring parties. However, this results in futures that hardly differ from the recent past. Regression models, for instance, would never have anticipated the precipitous drop in violence in Iraq due to the synergistic effects of the Sunni Awakening and the U.S. troop “surge” in 2007, when the Sunnis, squeezed on both sides by the extremist AQI and the newly empowered Shiite majority, decided to side with the United States against AQI (Biddle, Friedman, & Shapiro, 2012). Given that most forecasting of social and political systems occurs within a statistical modeling framework, more focused research is needed on aligning data processing with dynamics-based models.

It is not only the availability of more data that is important but also the intelligent processing of that data into quantities that are (a) theory-driven and (b) operationally relevant. The first criterion refers to the need for compact, low-dimensional quantitative representations that correspond to theoretical constructs from social science. The second refers to the need to include variables and parameters that can change on time scales of operational concern or can be influenced on those time scales using operationally available means. Imposing these criteria will facilitate model development and the practical application of computational models to forecasting. In such applications the models will address the issues most relevant to intelligence analysts and operational planners (thus tying into the Mitigate capability area) and can be used to forecast changes over a relatively small number of dimensions. Operational relevance has not been a strength of most extant instability forecasting work that relies on structural factors such as low economic development, regime type, ethnic fragmentation, mountainous terrain, existence of a territorial dispute, etc. These factors may predispose a country to conflict but indicate little about the situation-specific triggers, timing, and levers of influence that may exacerbate or ameliorate a conflict situation (O'Brien, 2010).

The insurgent network application presented above illustrates a theory-driven quantitative representation of soft, intangible variables for organizations. The definition of insurgent targeting policy – a one-dimensional measure – is motivated by social science research showing the importance of disagreement over targeting practices, such as indiscriminate attacks against civilians, in the relations between insurgent groups. The application of social identity theory to political rhetoric prompted the use of the conflict frame as an ideology variable. The theory’s definition in terms of in-groups and out-groups makes the data well suited to serve as input to models of alliance dynamics, as its correspondence to the formation of alliances among Iraqi insurgent groups makes clear. It can also be an input to models of insurgent strategic violence and is in fact correlated with targeting policy (Gabbay & Thirkill-Mackelprang, 2011). The number of parties to the conflict gives the dimension of the conflict frame vector, which can be further reduced by projection onto a master frame space, as described earlier in this chapter. Both targeting policy and conflict frames have operational relevance because they influence and reflect significant changes in the nature of the conflict itself and, hence, evolve on operational time scales. In addition, they can inform analysis and planning of operational means such as information operations or selection of particular groups for targeting or negotiations.

Additional types of data and improved processing techniques focused on elites and their organizations – whether in the government or its opposition, at a national or a local level – would be particularly helpful in developing theory-driven and operationally relevant forecasting methods. The decisions and actions of these individuals and groups directly and immediately shape the trajectories of crises and conflicts. The recent surge of research on popular opinion, driven by the availability of social media and automated tools for sentiment analysis, has overshadowed the significance of elites and their organizations. Although generic sentiment analysis software could be applied to the rhetoric of political leaders and organizations, it would likely not provide a useful data processing tool for forecasting their behavior. Standard sentiment analysis methods, originally developed for contexts such as movie and consumer product reviews, have not proven to work well on the discourse of political elites, whose rhetoric must often be circumspect and cast in neutral language, relying more on nouns and topic emphasis than on adjectives, which carry positive or negative sentiment in ordinary speech (Yu, Kaufmann, & Diermeier, 2008). However, researchers have used other types of text mining algorithms, such as support vector machines, to successfully classify elite political rhetoric (Diermeier, Godbout, Yu, & Kaufmann, 2012).

In support of this call for more research on elite and organizational data, it has been found that the presence of factionalism within a state plays a very significant role in forecasting political instability via statistical methods (Goldstone et al., 2010). This implies that accurate and timely metrics of elite or organizational factional dissension, like the conflict frame-based measure of ideological dissension in Figure 5(b), should improve forecasting of crises such as coups, rebellions, and civil wars. Researchers may find it particularly worthwhile to integrate data on elites with political event data that encode interactions such as violence between political actors. Automated methods for extracting event data from news feeds have been developed for various regions and contexts (Schrodt, 2012). In particular, some researchers have suggested the integration of event data with leadership rhetoric as a way to improve forecasts of the onset of intrastate conflicts such as insurgencies (Tikuisis, Carment, & Samy, 2013).

It is important to stress, however, that forecasting elite and organizational behavior should constitute a goal in its own right and not just an auxiliary input for conflict prediction. This will stimulate the development of such data at a greater temporal resolution, sufficient to track the evolution of these groups and more fully encompass the range of factors that drive their behavior. Elites respond to the preferences of their own organizational constituents, the actions of other organizations and their leaders, and the sentiment of the broader population. Standard social network analysis would focus on constructing ties only within the set of elites or between organizations, but researchers should develop data that enables representation of new multi-level networks, including the ties connecting leaders and the activist or rank-and-file components of their organizations as well as the ties among activists of different organizations.

The use of both leadership tie indicators (joint communiqués) and tactical unit tie indicators (joint operations) represents a step toward better representations of multi-level networks that can more fully account for elite policy and alliance dynamics. For example, it is possible that the standard mechanism of social influence, in which actors with strong ties grow more similar to each other (Friedkin & Johnsen, 2011), appears to be violated at one level but can be explained by ties between levels. Such a dynamic explains the shift of the IAI to a more extreme targeting policy in

the August 2007–July 2009 time period (Figure 6), even though its leadership ties in both periods were exclusively with Nationalist groups with more moderate targeting policies, which could have been expected to lead to a moderation of the IAI's targeting policy. This apparent violation of the social influence mechanism can be explained by the fact that the IAI was responding to dissent from its hardline rank-and-file constituents over its recent alliance with JAMI and HAMI (Gabbay & Thirkill-Mackelprang, 2010). The inclusion of the rank-and-file level can therefore account for forces on elites that could produce seemingly anomalous effects when viewed within a single-level network model.

Representations of multi-level networks should also include policies and ideologies. This calls for data that can be used to construct policy and ideological orientations of organizational membership elements. Social media could provide one source of data on rank-and-file opinions, as could analyst judgments. Another approach would involve looking at the rhetoric in media affiliated with elites whose audiences consist of their organizational members or support bases. For example, an analysis of the rhetoric of Afghan government elites found that the statements of the individual leaders themselves were often substantially different, and usually milder, than the rhetoric of their affiliated media, perhaps indicating the more hardline beliefs of their bases of support (Gabbay, 2011). This also highlights the value of incorporating into models data that connect elites with media outlets and media outlets with their audiences.

In conclusion, this chapter has highlighted aspects of the empirical implementation of computational models for forecasting purposes. The discussion has focused on dynamics-based models, which have the greatest potential to address the most operationally challenging and valuable types of forecasting questions but also make the greatest demands upon data processing. Quantitative variables and parameters for low-dimensional models must be coaxed from high-dimensional and often fundamentally qualitative data – a problem compounded by the often contested, chaotic, and covert nature of the environments and adversaries of most concern to national security intelligence analysts, planners, and policy makers. The analyst survey and rhetoric analysis methods described in this chapter represent two different approaches for tackling this problem. In practice, researchers who develop dynamics-based models for forecasting purposes often place a particular model formulation first and then seek to collect and process data appropriate for their model. Although this section has made a few relatively specific suggestions for future research, a broader recommendation would be to pursue a more integrated approach to developing dynamics-based models for forecasting. Such an approach should center on the construction of general quantitative variables appropriate for a particular domain, such as political unrest, insurgencies, or proliferation, which are sufficiently rich to enable the application of dynamics-based models (as opposed to purely statistical models), thereby encouraging a range of approaches that can be more readily evaluated.

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10 Computational sociocultural models used for forecasting[1]

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1. Introduction

This chapter provides an overview of computational sociocultural models that can support a Forecast operational capability. The nature and basis of the models that social scientists use differ across the various social science disciplines, and also differ from the physical models of traditional military simulation. Computational sociocultural models require the ability to represent and manipulate imprecise perceptual and cognitive concepts. This chapter provides an overview of how these models can account for natural vagueness of human thought and communication, along with the dynamics, complexity, uncertainty, variability, and unpredictability of actions and behavior, in order to generate forecasts.

Figure 1, inspired by a similar figure created by Zacharias, MacMillan, & Van Hemel (2008), illustrates the perceived similarities among several types of model forecasts. The models shown span methods based on mathematics to heuristics with probability, complex dynamics, soft methods and networks, and judgmental method subcategories. We selected these computational sociocultural models to represent a broad set of approaches, but the list is not exhaustive. Since 2008 (Zacharias et al., 2008), researchers have devoted considerable attention to analysis of online and social media data sources; where possible the forecast methods are discussed in relation to this type of data. The approaches covered in this chapter, organized in 9 sections, include probability forecasts based on (1) results from mixed-method aggregation, (2) emotions reflected in social media text, and (3) causal Bayesian methods. In addition, simulation model forecasts are reviewed including (4) system dynamics models, (5) agent-based models, (6) hybrid models, and (7) soft modeling methods, which include cellular automata, evolving self-organizing maps, and

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artificial neural networks. We also describe forecasts of (8) social networks generated from text analysis, and (9) judgmental forecasts, which include information sharing and collaboration, Delphi techniques, and prediction markets. Furthermore, Chapter 9 in this book discusses dynamic-based models and Chapter 11 describes cellular automata in more detail.

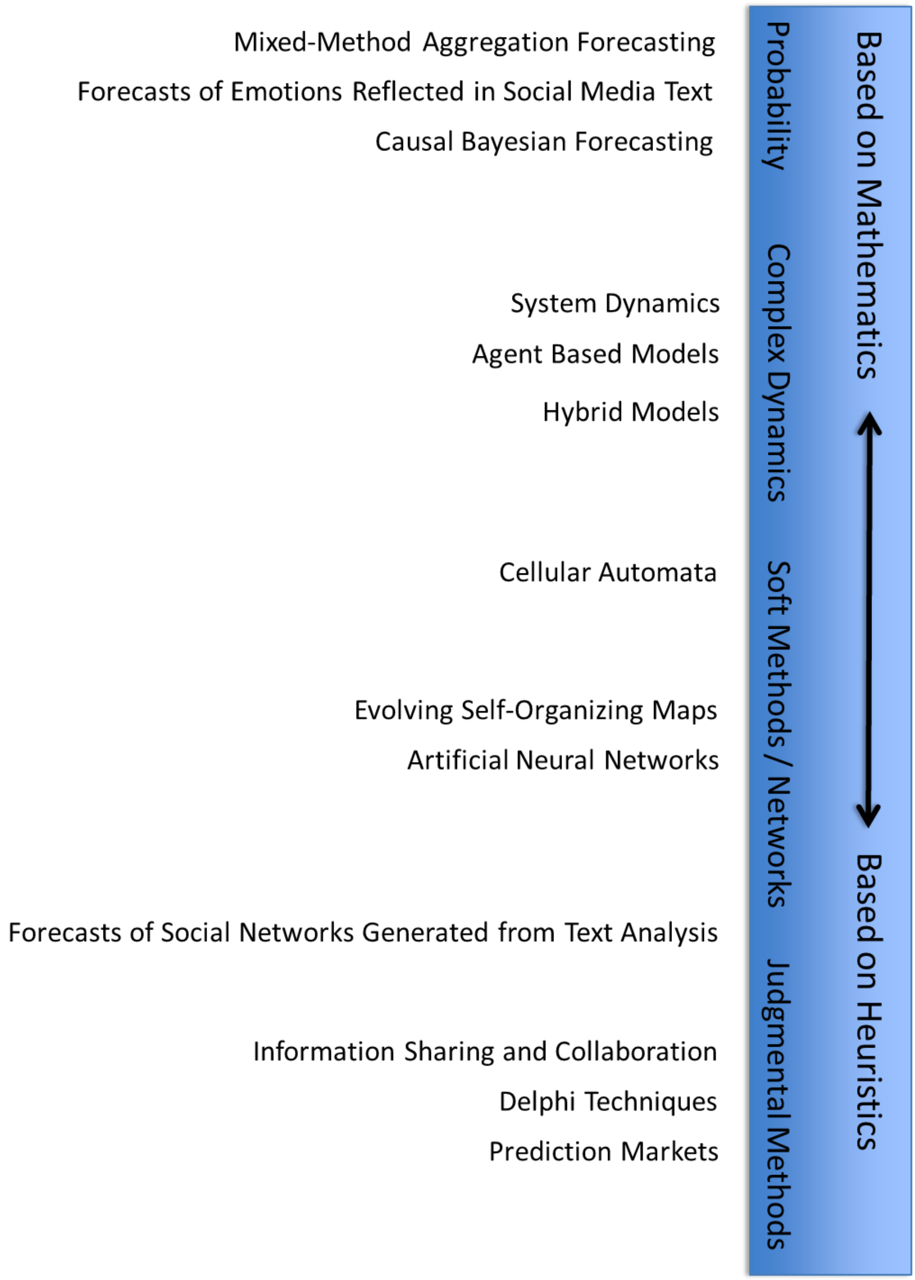

Figure 1. Forecast approaches based on mathematics, models, and heuristics.

2. Probability Forecasts Using Mixed-Method Aggregation

The Defense Advanced Research Projects Agency's (DARPA's) Integrated Crisis Early Warning System (ICEWS) project (2007–2009) demonstrated the possibility of forecasting select events of interest (EOIs) in 167 countries with high accuracy by using a mixed methods approach (O'Brien, 2010). Under Assistant Secretary of Defense for Research and Engineering ASD(R&E) funding (2010–2013) through the Office of Naval Research, the ICEWS team conducted further research, development, and operational testing and evaluation, leading to transition of ICEWS capabilities to a Department of Defense program of record.

ICEWS provides commanders with relatively low-cost, nontraditional methods of Intelligence, Surveillance and Reconnaissance (ISR) that assist commanders in generating, monitoring, and assessing Diplomatic, Information, Military, and Economic (DIME) courses of action to prevent or mitigate instability. ICEWS forecasts country stability for five EOIs: domestic political crisis, rebellion, insurgency, ethnic/religious violence, and international crisis.

ICEWS encompasses four primary sets of interoperating capabilities (Figure 2): (1) iTRACE— event trend analytics from news media and other sources; (2) iCAST—instability EOI forecasting; (3) iSENT—sentiment analysis from social media; and (4) iDIME—instability prevention and mitigation via DIME actions. The system integrates these capabilities through a web-based portal and a shared data repository. This section focuses on the computational social science models for forecasting that make up iCAST.

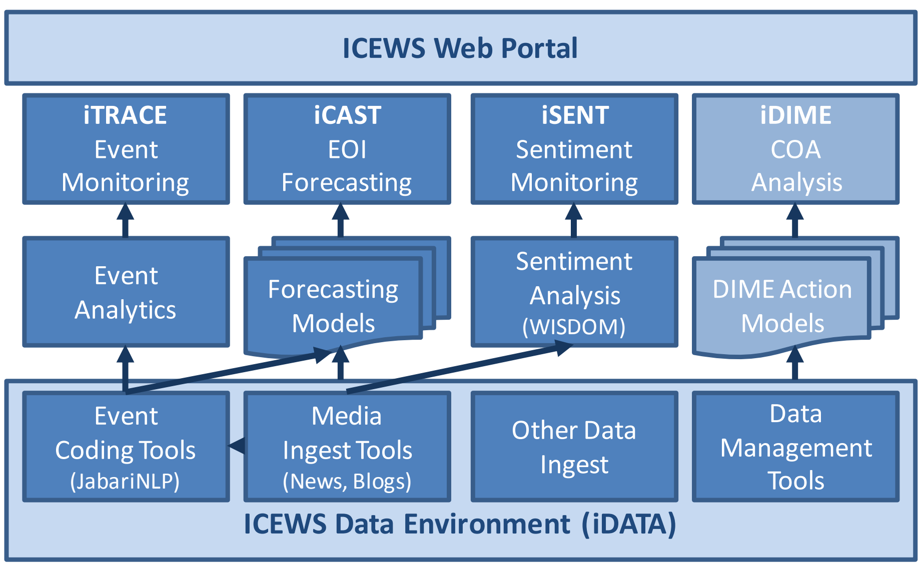

Figure 2. ICEWS Functional Capabilities.

2.1. iCAST Functionality

iCAST capabilities include an extensible, mixed-methods suite of computational social science models for forecasting EOIs. Models produce a monthly EOI probability for a given country for six months into the future. The mixed-methods approach integrates a number of statistical models for each EOI using a flexible model integration, data-provisioning, and execution framework called ADvanced Architecture for Modeling and Simulation (ADAMS) (Wedgwood, Horiatis, Siedlecki, & Welsh, 2009) and Bayesian methods for aggregating forecasts from those models for each country and EOI (Mahoney, Comstock, deBlois, & Darcy, 2011; Montgomery, Ward, & Hollenbach, 2011). These methods generate an aggregate forecast primarily by weighting each model's current forecast by its prior performance as compared to a ground truth data set (GTDS) based on subject matter expert assessment of whether or not an EOI occurred in a given country in a given month. The iCAST team used the GTDS set covering 2000–2012 to calibrate the statistical models and validated them using a split sample methodology. Validity testing showed that the aggregate forecast generated by the model ensemble outperformed that of any of the individual models (O'Brien, 2010).

Within iCAST, statistical models include logistic regression (logit) models that combine traditional, relatively static, country-level indicators (e.g., level of democracy, gross domestic product, ethnic fractionalization) with more dynamic aggregations of event data coded from a large corpus of news stories dating back to the year 2000. These models capture structural conditions that may predispose countries towards instability and behavioral factors such as recent interactions among government, insurgent, and other types of actors. iCAST also includes hierarchical statistical models that exploit networks of relationships among countries such as spatial proximity, trade ties, people flows, etc. (Ward et al., 2012). Because instability can "spread" over such networks, EOIs in two countries related by a network may not be truly independent. In addition, iCAST contains zero-inflated negative binomial regression models that accommodate the frequency of non-events (i.e., zero-valued events). Furthermore, the constituent statistical models often complemented one another, with some performing better on certain EOIs and countries than others. In later phases, model performance improved from around 80% accuracy (number of correct predictions) to over 95%, with less than 5% false positives.

2.2. Analyses Supported

iCAST increases users' awareness of human, social, cultural and behavioral (HSCB) characteristics describing the historical, current, and projected sociocultural situation in a country. The forecasts themselves are essentially heuristics that guide users as they search the massive space of HSCB data.

At the most basic level, iCAST enables users to view forecasts for different countries and/or EOIs to explore such questions as, "What is the anticipated probability of an insurgency in Country X?" The distribution of probabilities for a particular <EOI, country> pair can help users to identify forecasts that merit deeper investigation. In Figure 3, forecasted probabilities are shown as an orange line. The plot area for historical data points are shaded either black (event occurred) or white (event did not occur). For forecasts, the plot area is shaded depending on forecasted probability where red

are high-probability events (>=67%), yellow are medium-probability events (>=33% and <67%), and green are low-probability events (<33%).

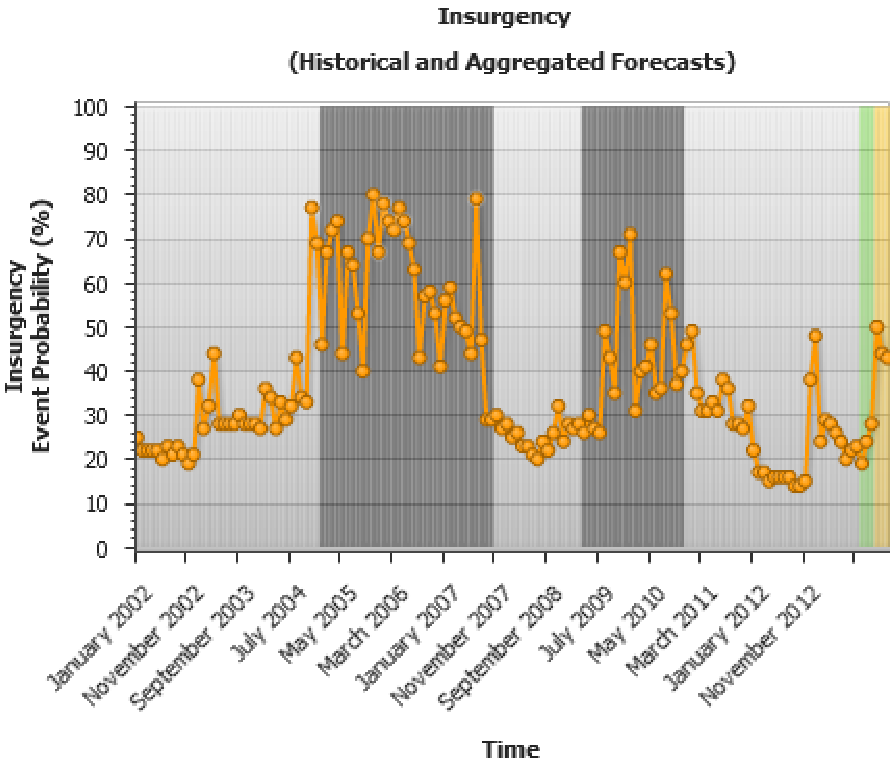

Figure 3. iCAST showing aggregated forecasts generated for country-level insurgency**.**

Once the user has chosen a forecast for further examination, iCAST decomposes the aggregate forecast to permit analysis of individual model forecasts. This drilldown informs the user how each individual forecast contributes to the aggregate (Figure 4). The table at the top of Figure 4 shows the models contributing to the aggregation and the aggregate model itself. The table also lists individual model forecasts and impact for each model. In this example, Model 4 has the greatest impact on the aggregate forecast. The bottom of this view shows the accuracy (blue), precision (red), and recall (green) analysis for each model.

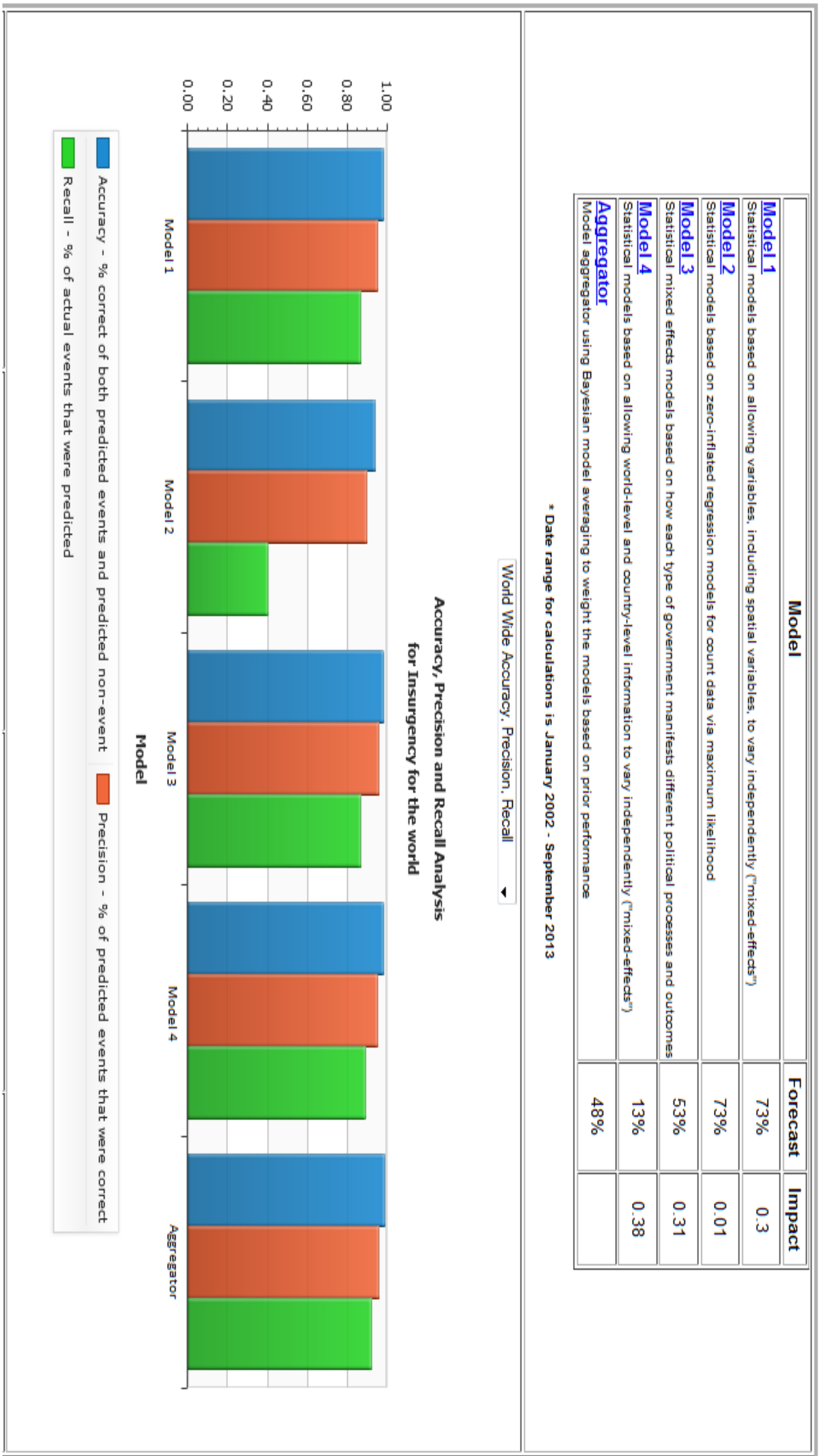

Figure 4. "Aggregated Forecast Drilldown" view for a specified country, EOI, and time (i.e., month and year).

When the user identifies a specific model for further analysis, iCAST enables a more detailed exploration with respect to the underlying data parameters informing the model's forecasts. For example, the user may ask, "What key factors contribute to the likelihood of an insurgency's occurring, or not, in a country?" The visualizations show the user the variables used by a model, how those variables have changed over time with respect to occurrence of the EOI, and which variables have impact on the current forecast calculation (Figure 5).

iCAST analyzes the impact of each variable on the model's forecast by performing sensitivity sweeps in which a single variable is varied discretely over a historically observed range of values while all other variables are left at their currently observed levels. If fluctuations in a specific variable alter the model's forecasted probability (<=0.2%), the variable name is shaded blue. If it alters the probability slightly (>0% change, but <2% change), the variable is shaded yellow. If changes in the variable value produce no change, the variable is shaded gray.

To help users better understand the variables used by the models, iCAST permits drill down into a view of the variable's performance over time. From this view, the user can identify a particular value of the variable to investigate further. Furthermore, iCAST enables the user to access the news stories from which the model extracted events that contributed to the calculation of a particular variable.

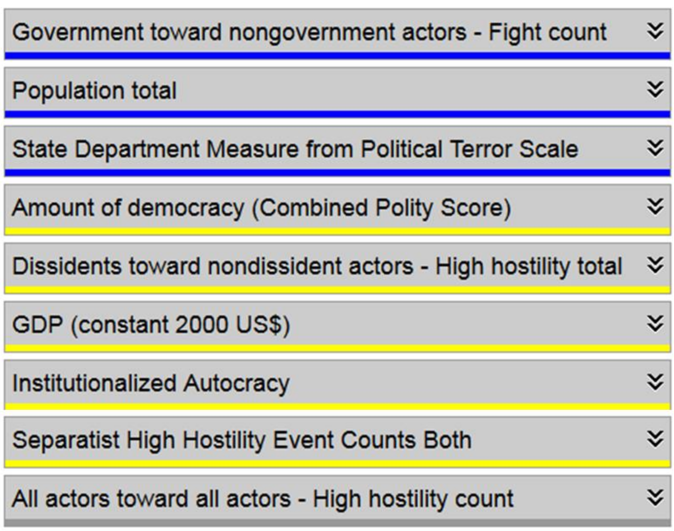

Figure 5. Screenshot of the variables list of a specific model presented to better understand what factors contribute to the model's analysis.

2.3. Modeling Considerations

Operators are particularly interested in the onset and cessation of EOIs (e.g., when a rebellion starts or ends)—a subset of the already sparse set of occurrences of the EOIs, and therefore hard to forecast with accuracy. Operators also prefer statistical models that use actionable indicators (i.e., variables that are able to be influences by DIME actions) grounded in social science theory as

input. The relatively rare occurrence of the focus EOIs in the GTDS makes it difficult to identify actionable indicators.

In addition, operators prefer models that accurately predict EOIs in multiple countries over those focused on just one country. This led the iCAST team to develop mixed effect models in which the coefficients of some variables can vary by country. The team also created models for sets of countries grouped by polity type (e.g., democracy, autocracy, etc.). These techniques improved model performance and actionability.

Models must foster operators' trust in the results by providing actionable detail from the forecasts. In iCAST, the complexity of using an aggregated forecast made up of multiple, heterogeneous models complicates transparency. Presenting the aggregated model results in a useful way required three interrelated capabilities: (1) understanding what data the models use (including how model inputs are calculated), (2) understanding the social science theory underlying the models and their inputs and outputs, and (3) presenting the aggregated and individual forecast results to support traceability in a clear and easily navigable user interface.

To this end, the iCAST team developed a framework for model forecast transparency (Wedgwood, Ruvinsky, & Siedlecki, 2012) that reveals the driving variables of each model, shows how those variables performed under historical conditions, and supports exploration into how changing conditions may affect forecasts. Interactive visualizations, such as those shown in Figure 6, generally provide that transparency for end users (operators, analysts) and model developers. These views include heat maps showing forecasted EOIs and details on aggregate forecasts (from the aggregation methods) and on individual model forecasts, including which input variables (and values) had what impact on each model's forecast.

iCAST supports a "what-if" capability for exploring how fluctuations in model inputs affect the forecasted probability generated by the individual, constituent models as well as the aggregate model. Identifying the variables at play in an individual model forecast can lead users to inquire how changing those variables might affect the probability of an EOI. iCAST lets users explore data parameter sensitivity within a specific model forecast (Figure 6) to see how changes in a variable affects the individual model's forecast. iCAST also supports exploring how the impact on the individual model forecast then influences the aggregate model's assessment.

Some of these visualizations also permit "what if" exploration (Figure 7): allowing users to alter the values of model input variables and observe the resulting impact. This enables users to gain an intuitive feel for the relationships among the input variables and model output. Users can also simulate DIME actions and their impact on EOI probabilities by altering these "levers." Other transparency views display a model's pedigree, track record of accurate predictions, etc.

Figure 6. Potential impact of model input variables on probability of an International Crisis in a specified country and time period. This view shows that the variable “Government human rights violations” (GHRV) can impact the current EOI forecasted of 0.86.

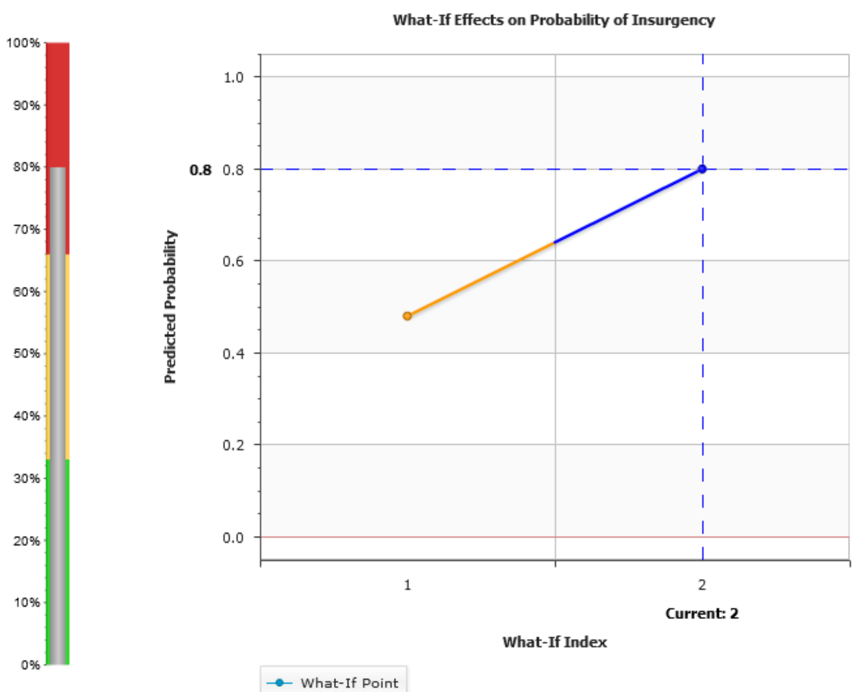

Figure 7. iCAST visualization allows users to investigate "what-if" scenarios. This view shows the current value of all model variables and forecasted probability in orange. The user can manipulate levels of each variable to see how changes in variable values affect the EOI probability shown in blue (variable changes increase the forecast from 0.5 to 0.8).

An ontology of epistemological elements that captures model design from the underlying theory has been developed and operationalized with specific data sources to improve model verification and validation (Ruvinsky, Wedgwood, & Welsh, 2012). iCAST has used such an ontology to extend information and understanding regarding model designed and performance.

3. Forecasts of Emotions Reflected in Social Media Text

Researchers have developed new methods to characterize the dynamics of emotions in large populations as captured in Twitter data (Servi, 2013; Servi & Elson, 2012). To cull the right subset of Twitter data, researchers must first specify the dates, hashtags, key words, and/or geographical region(s) of interest. Second, as shown in Figure 8, they must convert the words of Twitter messages into numerical data as shown on the y-axis. This can be done using a bag-of-words approach. Here the researcher formulates a collection of words – "the bag" – associated with an emotion of interest and compares them to the actual words in the tweets to compute a score for each day and for each emotion. This can be done by associating an intensity of the emotion, sometimes referred to as a "valence," with each word (e.g., Bradley & Lang, 1999; Dodds & Danforth, 2010) or by treating each word with the same intensity. Linguistic Inquiry and Word Count (LIWC), a bag-of-words approach that has an extensive scientific pedigree and has been validated across a number of studies (e.g., Pennebaker, Booth, & Francis, 2007; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007; Pennebaker & Francis, 1996), was used to generate Figure 8.

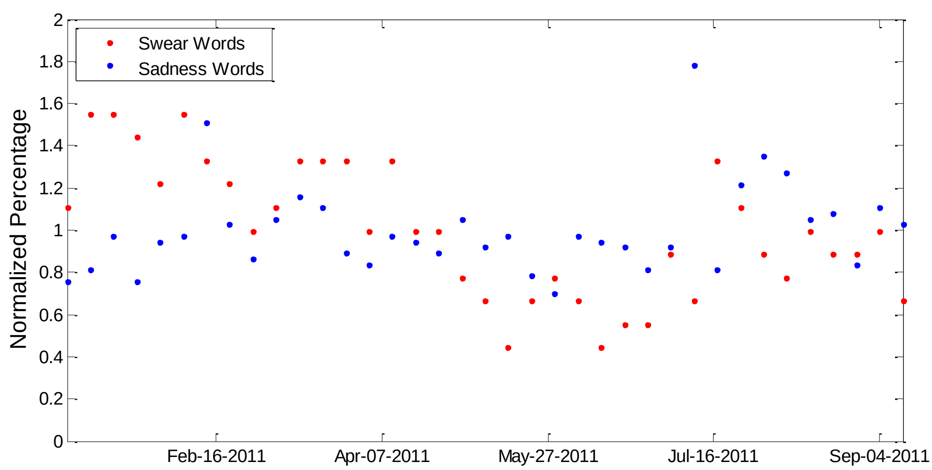

Figure 8. Normalized percentages of LIWC swear and sadness words in weekly aggregates of tweets.

While bag-of-words approaches rely on word distributions and can also use co-occurrence associations to tease apart the possible meaning of words in text, a different approach seeks to

extract meaning by considering the role of words within the structure of the phrase or sentence. The annotated Multi-Perspective Question Answering data set (Wiebe, Wilson, & Cardie, 2005) captures details about the sentiments and opinions expressed by or attributed to opinion holders, the intensity of those sentiments, and the propositions or entities toward which these sentiments are directed. This approach was used to annotate each word, phrase, and sentence within some 600 news and editorial articles, enabling words-in-context approaches to sentiment analysis to be trained and evaluated against this data set (Day, Boiney, Ubaldino, & Brown, 2012; Kim & Hovy, 2006; Wilson, 2008). Pang and Lee (2008) provide an overview of Natural Language Processing approaches to sentiment analysis.

The third step, illustrated in Figure 9, requires algorithmically filtering some of the measurement error. This neccesates a model of the dynamics of emotions. Servi and Elson (2012) postulate that emotions follow piecewise linear dynamics until an event external to the system creates a discontinuous change – in essence an emotional "reset" – after which the dynamic resumes. The authors use the term "breakpoint" to describe this discontinuous reset. Researchers have developed algorithms for such a filtering approach, as well as a number of generalizations of that approach (Servi, 2013).

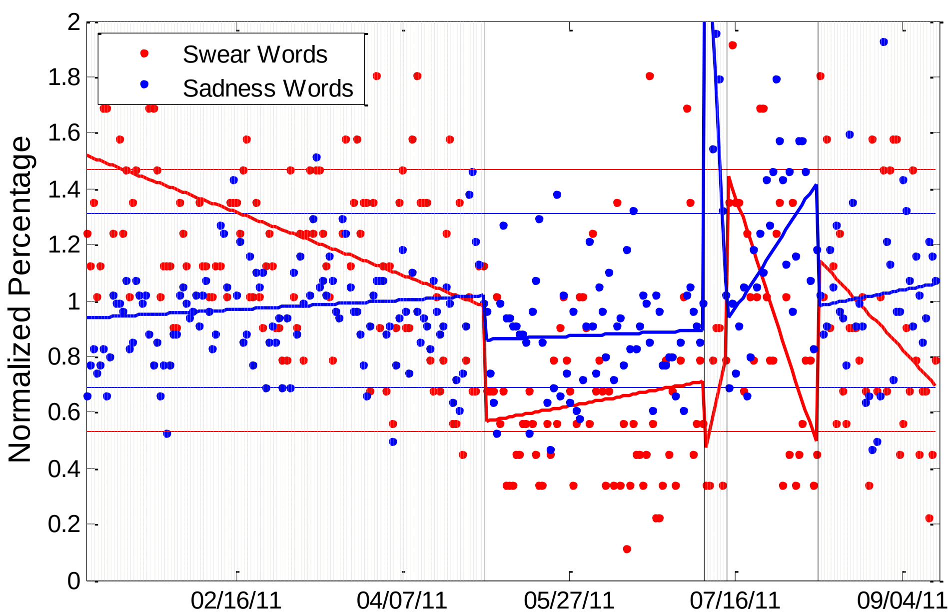

Figure 9. Breakpoint analysis of normalized percentages of LIWC swear and sadness words in daily aggregates of tweets, using a linear model.

Forecasting efforts seek to predict future *events* using input along the lines of Figure 9 in a scientifically rigorous manner. Predicting future LIWC data scores represents a first step in this direction. This requires that predictions be compared to a baseline. The natural baseline is to assume that future emotional intensities would be the same as those in the past. More formally, the baseline is:

Rule 1: Use the last dot. Forecast the value of a LIWC indicator without using breakpoint analysis by assuming that the last data point is the best estimate for the future. If this rule outperforms the others, it will mean that breakpoint analysis is not necessary.

This rule was compared with two other rules (Servi & Elson, 2012):

Rule 2: Project ahead. Perform a breakpoint analysis with the linear model and use that analysis to make forecasts by projecting ahead in time, starting from the most recent breakpoint. That is, extend the most recently derived trend line (continuing along its current slope) and use that line to determine the predicted value. This is the most natural approach. However, as indicated below, it may demonstrate a comparative advantage only if extensive data exist in each individual breakpoint region and if the trend lines have large slopes.

Rule 3: Use the last estimate. Perform a breakpoint analysis with the linear model and use that analysis to forecast that future values will be the same as the last estimated data point in time. Extend the most recently derived trend line, but with a horizontal slope, rather than continuing along the current slope of the line. While this may be less accurate and less intuitive than Rule 2, if data are plentiful, this more conservative and robust rule will perform well for a broader range of data availability and slopes of the trend lines.

Table 1 illustrates the result of a typical study (Servi & Elson, 2012) that represents analysis using the two datasets (swear and sadness words) illustrated in Figure 8 and Figure 9. After a warm-up period of 100 days the researchers made predictions 1 day, 8 days, and 15 days into the future and compared the prediction with the actual data. While the results call for more validation, the key finding depicted shows that for these data Rule 3 consistently outperformed both the baseline Rule 1 and Rule 2. In addition, Rule 2 outperformed the baseline Rule 1 when applied against the normalized swear word data but fell short when applied against the normalized sadness data (not normalized to tweet volume but to each other). Table 2 lists the sum of the square of the difference between the percentage of LWIC words predicted compared with the actual number.

Table 1. *Sum of square error analysis in predicting normalized LIWC swear words for daily data*

	1 day	8 days	15 days
Baseline rule	42	50	52
Project ahead rule	37	43	49
Use last estimate rule	34	35	35
Improvement	19%	35%	35%

Table 2. *Sum of square error analysis in predicting normalized LIWC sadness words for daily data*

	1 day	8 days	15 days
Baseline rule	17	25	29
Project ahead rule	25	49	69
Use last estimate rule	17	22	22
Improvement	0%	12%	24%

Rule 2 might have performed relatively poorly because the linear rate of change of LIWC scores with respect to time is imperfectly estimated. Hence, a large component of the prediction error of Rule 2 may result from the error in estimating the rate of change of the LIWC scores, and in some cases that misestimation may dominate it. Therefore, Rule 2 might perform better as the number of data points in the breakpoint region increases, the rate of change in the LIWC scores increases in absolute value, and/or the error in the LIWC estimates decreases. The structural nature of this source of error has been recognized in the literature (Servi, 2013; Tibshirani, 1996).

Research has just begun to examine another, more fundamental challenge to forecasting through modeling of emotions: the dynamics of emotions may be inherently nonlinear. This would have profound implications, such as:

- The accuracy of linear forecasting models, such as those described above, may be self-limited. The limitation could be quantified by proper examination of the nonlinear dynamics.

- The accuracy of forecasting could be improved beyond the best linear forecasts by estimating the characteristics of nonlinear dynamics data and using them to create new forecast models.
- Exploring characteristics found only in nonlinear dynamical systems, such as the phenomenon of Critical Slow Down (CSD) before abrupt changes observed in many domains with nonlinear dynamics, could lead to a different class of forecast models (Drake & Griffin, 2010; Scheffer et al., 2009; Slater, 2012).

4. Causal Bayesian Forecasts

A forecast is a statement of the probability that a proposition will hold at a given point in the future.[2] Researchers can use statistical models for forecasting provided they have assembled a large data base of indicators containing positive and negative examples of the proposition of interest. For example, a statistical forecasting model might outperform random guessing at computing the probability it will rain tomorrow based on today's temperature, relative humidity, cloud cover, and so on. In situations characterized by known trends related to the question of interest and the availability of reliable time series data, researchers can build auto-regression forecasting models such as those used to forecast macroeconomic conditions (Granger, 1969). The U.S. Commerce Department forecasts the coming quarter's Gross Domestic Product based on the prior quarters' housing prices, unemployment rates, etc.

However, statistical forecasting cannot predict rare events (e.g., the probability that al-Qaida will develop an improvised nuclear weapon by 2015) because the required large database of prior examples does not exist. Further, statistical methods cannot identify or predict the impact of interventions (e.g., how that probability would change if U.S. forces expelled al-Qaida from safe havens in Africa) unless the model contains causal factors. For example, the National Weather Service does use statistical models based on causal factors such as wind patterns and barometric pressure to forecast events such as the point of landfall of a hurricane.

Predicting rare events and the impact of interventions requires modeling of causal chains of actions and events. Researchers who study causality use "neuron diagrams" to represent cause-effect relationships. For example, Figure 10 depicts a model of possible causes of a carpet becoming soaked with water from an aquarium.

[1] This exposition uses the terms "forecast" and "prediction" interchangeably.

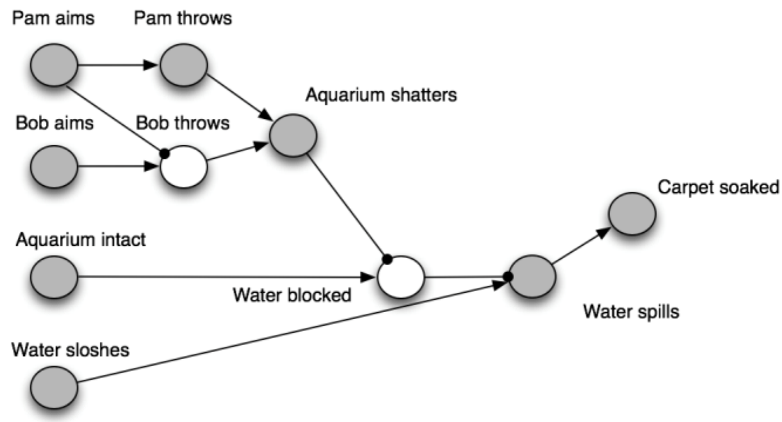

Figure 10. Causal Network.

Causal models result from enumerating possible sequences of actions that might lead to various outcomes. Because planning consists of deliberating to construct a chain of actions that would bring about a desired state, a plan is a kind of causal model: actions cause effects (usually with some uncertainty) and some of the anticipated effects of actions either constitute the goal of the plan or establish preconditions for subsequent actions that eventually bring about the goal. Plans typically are represented by Kripke networks (Kripke, 1963), which can be imagined as a neuron diagram having choice points and branches leading to various outcome states, including the goal state and various ways the plan might fail to reach the goal state.

In the absence of a deterministic cause-effect relationship (e.g., throwing a rock at an aquarium does not always cause the glass to shatter; stopping rock throwing does not guarantee the carpet will not be soaked), neuron diagrams (or plan networks) can be augmented with state transition probabilities. This transforms a causal network into a Causal Bayesian network (CBN) (Pearl, 2000). When nodes represent random variables and edges represent conditional dependencies among the variables, the directed acyclic graph is called a Bayesian Belief Network (BBN). As illustrated in Figure 11, each node that has at least one parent node has an associated conditional probability table in which rows correspond to a combination of parent node states. The values in each row constitute the conditional probability distribution over the node's states given an enumerated combination of parent node states. A node with no parents means the random variable is independent of the other variables in the network (e.g., node C – cloudy). Parentless nodes contain the unconditional prior probability distribution over that node's states.

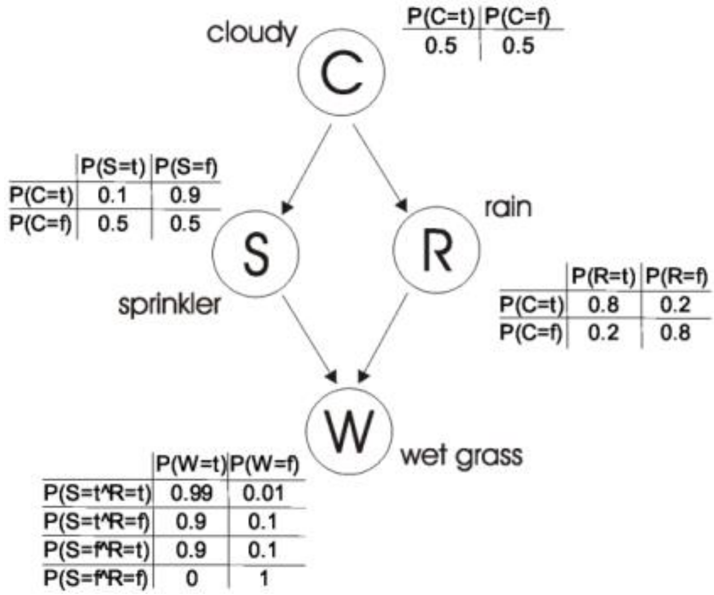

Figure 11. Bayesian Belief Network.

Such graphs are called BBNs because they use Bayes' rule to compute the belief of every state of every node in the network. In this example, probability (P) is the belief that a state holds, whereas a statistical model would compute the frequency with which the outcome state occurred (e.g., it rained) in relationship to the number of times the given combination of factor values was observed (e.g., the weather was cloudy and hot on the previous day). These beliefs are updated upon observation of any combination of states of the variables represented by the network. For example, in the BBN in Figure 11, if the modeler knows that the grass was not wet on a given day, then the probability that it was cloudy on that day would decrease from 0.5 to 0.36, the belief that the sprinkler was on from 0.3 to 0.06, and the belief that it rained from 0.5 to 0.12.

Importantly, providing evidence in *any* node in a BBN updates *all* the other state beliefs. Thus, BBNs can be used for evidential reasoning (e.g., dry grass is evidence that it was not cloudy, that it did not rain, and that the sprinkler was not used) and for prediction (e.g., looking out of a window and observing a cloudy – or sunny – sky allows individuals to assess the probability that they will encounter a running sprinkler or wet grass later in the day).

A BBN becomes a causal Bayesian model when some of the nodes represent actions, their effects, or preconditions, and the links represent causal relationships such as those in a neuron diagram. One can create a causal model using subject matter expertise. Adding the probability that each action will succeed given the possible states in which the action is selected for execution turns that structure into a Causal Bayesian Network (CBN). CBNs can be used to analyze courses of action (COAs) – another term for plans. Thus, CBNs that represent plans can be used to forecast the possible outcomes of the plans. COA analysis involves representing a plan as a CBN and using the

causal structure of the CBN to identify the outcome of interventions, such as stopping key actions by negating their preconditions. A CBN representation can help to predict if an agent will follow a particular plan by using plan recognition technology to generate possible explanations in the form of plans derived from observed evidence. This becomes particularly valuable in situations where adversaries actively attempt to deny information to observers (Burke, Coplon, Elsaesser, Hitzelman, Mireles, Rothleder, & Tanner, 2005).

5. System Dynamics Forecasts

System dynamics is a simulation approach used to simulate the behavior of a system over time as a consequence of its top down design and causal relationships. It has proven useful in modeling organizational behaviors driven by complex causal structures. Since its first application to modeling production and distribution dynamics in industry (Forrester, 1958), researchers have applied system dynamics to simulate organizational behavior, both to create generalized theory (Repenning & Sterman, 2001) and to model specific systems for forecasting, policy development, and design recommendations (Lyneis, 2000). In addition, system dynamics has been used to study such areas as strategy (Fowler, 2003), supply chains (Scheiritz & Größler, 2003), product development (Ford & Sterman, 1998) and business processes (Ashayeri, Keij, & Bröker, 1998).

The system dynamics modeling approach can serve as a hands-on organizational learning tool to help managers discover and understand the structures underlying the dynamics of their organizations. “Flight simulator” models of organizations are often used to help teach systems thinking by building up simulated experiences of complex systems (Fowler, 2003; Sterman 2000). Vennix (1998) has developed a corresponding group facilitation approach to simultaneously allow group participants to create qualitative “causal loop diagrams” and quickly test the implications of the feedback logic of those diagrams with small system dynamics simulations. Modelers can then build and validate more advanced system dynamics simulations that use this information to make forecasts or design strategies to create new models of behavior in real-world systems.

All but the most complex system dynamics simulations run in near-real time, enabling users to perform “what if” analyses rapidly and easily. The causal structure of system dynamics models also allows decision makers to quickly identify the key policy levers that control system behavior. The C-ROADS model of global climate change (Sterman et al., 2012) presents one example of such a model.

System dynamics uses simple diagrams to represent the causal dependencies in a system. The diagrams present processes in terms of “stocks” (e.g., people, materials, knowledge, money), materially conserved “flows” between the stocks, and causal information about stocks and parameters that determine these flows. Users populate these “stock and flow diagrams” with data to simulate the behavior of a system, as illustrated in Figure 12, a simple model of disease dynamics. Flows (double-lined arrows) and information arrows (single-lined arrows) connect stocks, variables, and constants. The polarity of these causal connections is shown as either a “+,” to indicate a positive relationship, or a “–,” to indicate a negative relationship.

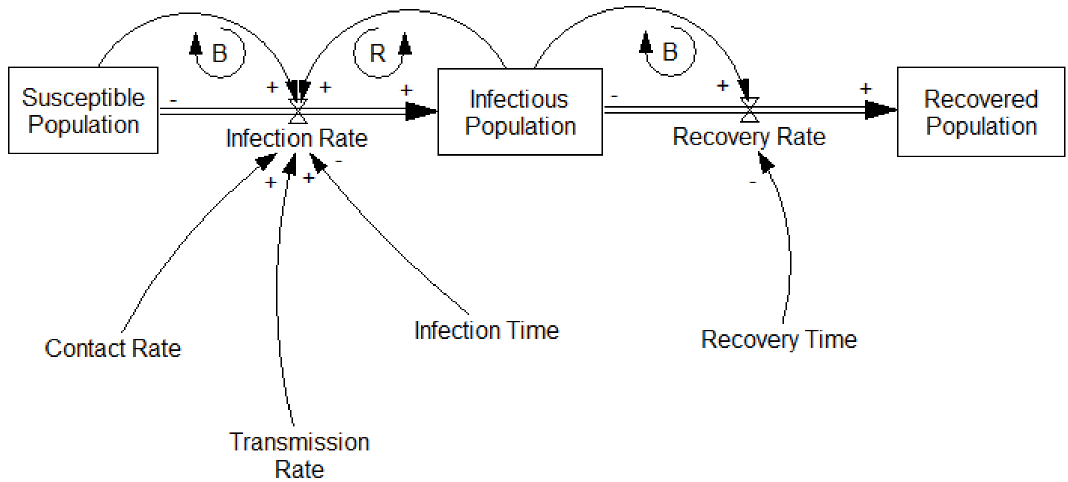

Figure 12. System dynamics depiction of the Susceptible, Infectious, Recovered (SIR) model of epidemiology.

The behavior of system dynamics models is driven mainly by feedback loops. In Figure 12, a powerful reinforcing "R" feedback loop allows the system to rapidly increase the Infection Rate when the stock of Susceptible Population is large. This occurs because the larger the Infectious Population, the more likely its members are to have contact with the Susceptible Population. Similarly, two balancing "B" feedback loops limit and ultimately end a wave of infection. If the Susceptible Population decreases, it contains fewer people to infect. If the Recovered Population increases, it means that more people are no longer susceptible to infection.

The model shown in Figure 12 is a very simple one. Complex feedback systems can be modeled by using more variables and linking them to form more feedback loops. No matter how complex, however, the behaviors of these models can be broken down into classic dynamic patterns of behavior, such as exponential growth and decay, S-shaped growth, growth and collapse, and oscillatory behavior.

Because system dynamics fundamentally relies on modeling the causal dependencies in a system, modelers must have a firm mathematical understanding of each of these relationships, as well as supporting data and metrics if the system is to be simulated. However, quantitatively capturing these relationships in system dynamics models of "soft" processes, such as strategy, presents considerable challenges. System dynamics models force modelers to explicitly link data and causal structures throughout the system. This can also aid in uncovering problems related to data collection and model structure.

Calibrating models with historical data and/or running a sensitivity analysis (e.g., Monte Carlo) may help alleviate or highlight concerns with both input data and model structures of abstract concepts. By conducting a sensitivity analysis, a modeler can determine whether a system has "tipping

points" or extreme sensitivity that must be discovered and managed. A Monte Carlo analysis generates a range of estimated future values for a variable, rather than point-in-time values for individual model runs. The output of this analysis can be visualized as a "hurricane chart" that displays a confidence range in model output over time, as shown in Figure 13.

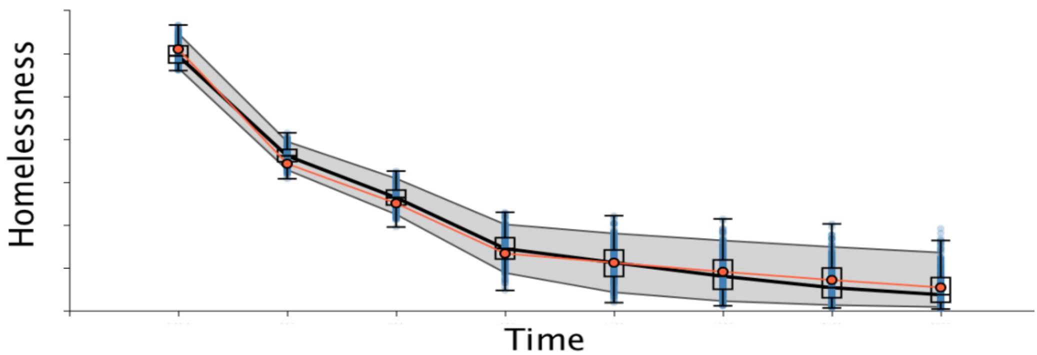

Figure 13. Example of a Monte Carlo analysis showing the range of values of a stock in a system dynamics model. Uncertainty, shown in the shaded area, grows over time. The orange line is one of the hundreds of runs used to compute the area of uncertainty.

5.1. System Dynamics for Forecasting

The literature describes many examples of using system dynamics for forecasting, especially for various forms of demand (Niu & Gillard, 1994; Tharmmaphornphilas, Loharsiriwat, & Vannasetta, 2012; Najjar, 2013). Tharmmaphornphilas, Loharsiriwat, and Vannasetta (2012) compared their results to that of a Box Jenkins (1970) forecast and attributed their improved prediction results to the inclusion of qualitative influences ignored by other methods and of interactions and feedback in the system that are not apparent from an analysis of the data alone.

System dynamics is best used for forecasting models where the *causal structure* of the system, rather than its initial parametric conditions, drives system behavior ("structure drives behavior"). If researchers have no solid hypothesis to support an underlying structure that drives a system's dynamics, data-driven approaches such as regression are more appropriate. System dynamics models are generally better suited to providing strategic insight into problems and for comparing alternative policies than to making point predictions subject to noise and externalities.

5.2. System Dynamics Challenges

To perform effectively, system dynamics models must incorporate all the feedback loops and variables relevant to understanding the problem. Models of management systems, for example, must capture concepts such as "schedule pressure," which can lead to lower quality and then an increase in re-work, thereby slowing production. Because of the focus on causal structure, missing such a causal loop can greatly alter the model's behavior. System dynamics modeling only produces

useful results when the assumption of aggregation is plausible. If the stocks consist of heterogeneous individuals or resources, and if this heterogeneity is important to system behavior, a system dynamics model may provide misleading results. The reliance on aggregate representations of entities in system dynamics makes it easy to implement models of high-level system structure, but complicates low-level modeling. System dynamics modelers have responded to this weakness by increasing the number of stocks or states used in their models, but this makes models more complex, harder to debug, and harder to explain to users.

6. Agent-Based Model Forecasts

Fundamentally, an Agent-Based Model (ABM) is a simulation, and, like all simulations, can take many forms. Typically, modelers create these simulations using a modern computer programming language such as Java, but they could also create an ABM using ball bearings, animals, or even human actors.

ABMs differ from many other simulations in the way they focus on the system studied: they *explicitly* represent all of the *relevant* entities and their *interactions* within the system. This makes them especially useful for representing and studying human systems, which may involve many different kinds of actors with a large amount of heterogeneity.

At the very least, ABMs consist of agents (discrete purposive entities, such as humans), a meaningful environment (typically a geospatial environment, but sometimes a more abstract space), and a set of rules that define interactions (among agents and, potentially, among agents and the environment). Often the interaction rules contain random components, meaning that two agents *may* interact, but that interaction is not guaranteed. This, in turn, means that each run of an ABM is unique. Therefore, to understand the results users must run the ABM many times, varying the random conditions. General information about ABMs and their use can be found in: *Artificial War* (Ilachinski, 2004), *Agent-Based and Individual-Based Modeling* (Railsback & Grimm, 2012), *Simulation for the Social Scientist* (Gilbert & Troitzsch, 2005), and *Growing Artificial Societies* (Epstein & Axtell, 1996).

6.1. Advantages of Agent-Based Models

For certain applications, ABMs have advantages over traditional methods used to study human systems. For example, traditional systems dynamics and differential equations disregard space, meaning that all the humans represented in these systems are at the same place at the same time and everyone interacts continuously with everyone else. Furthermore, only very strong assumptions about human rationality and problem-solving abilities enable modelers to solve the calculus used in economic models. By contrast, ABMs can represent humans in a more natural way, known as “bounded rationality” (Simon, 1972). In these models humans can behave like humans and make mistakes, come to incorrect conclusions, have prejudices, and act based upon incomplete information.

Just as important, unusual events and rare individuals – so-called outliers or “black swans” (Taleb, 2010) – can have a profound impact on the system. Many other analytic tools used to study human

systems ignore or define away these outliers. This can make the impact of rare events such as terrorism or the influence of unusually charismatic individuals, *as part of a "normal" population*, very difficult to understand, and highlights the shortcomings of representing heterogeneous systems in analytic tools other than ABMs.

6.2. Using Agent-Based Models

Like all simulation and analytic tools, ABMs can be used correctly or incorrectly. Two important frameworks have been built up around the use of ABMs: "docking" (Axtell, Axelrod, Epstein, & Cohen, 1996); and "Levels of Empirical Relevance" (LER) (Axtell, 2005). Docking describes how well an ABM relates to a reference. As shown in Figure 14, there are three levels of docking: Identity (the ABM produces results identical to the reference), Distributional (the ABM produces results *statistically* indistinguishable from the reference), and Relational (the ABM behaves in a manner consistent with the reference but the results are *statistically* distinguishable). LER has four levels. At Level 0 the agents within the ABM behave in a plausible manner for a given domain. At Level 1 the ABM produces overall reasonable dynamics; e.g., firms of different sizes exist in an artificial economy. At Level 2 the ABM produces the correct overall structure; e.g., the distribution of firm sizes in the artificial economy corresponds to the distribution in the real economy (Axtell, 2001). Finally, at Level 3 the ABM produces correct results at the *individual* level; e.g., the artificial firms represent real firms and both firms are the same size.

As the figure shows, combining docking and LER creates a framework that guides how carefully researchers must evaluate the ABM and how much time and effort it will take to create the ABM. At present the data requirements for Level 3 LER (correct results at the *individual* level) are so onerous that it is very unlikely that an ABM can be created to achieve this level. Advances in big data, data sharing, and social computing will mitigate this limitation; however, for many topics and regions of national security interest the constraint will persist for some time. Researchers must also take the scale of the system and of the ABM into account. These sorts of systems can change their behavior as the number of entities increases (for example, a single water molecule cannot produce "wetness"; that property only belongs to large groups of water molecules). The same is true for ABMs: an ABM cannot be considered satisfactory until it functions correctly at the same (or as similar as possible) scale as the system being studied.

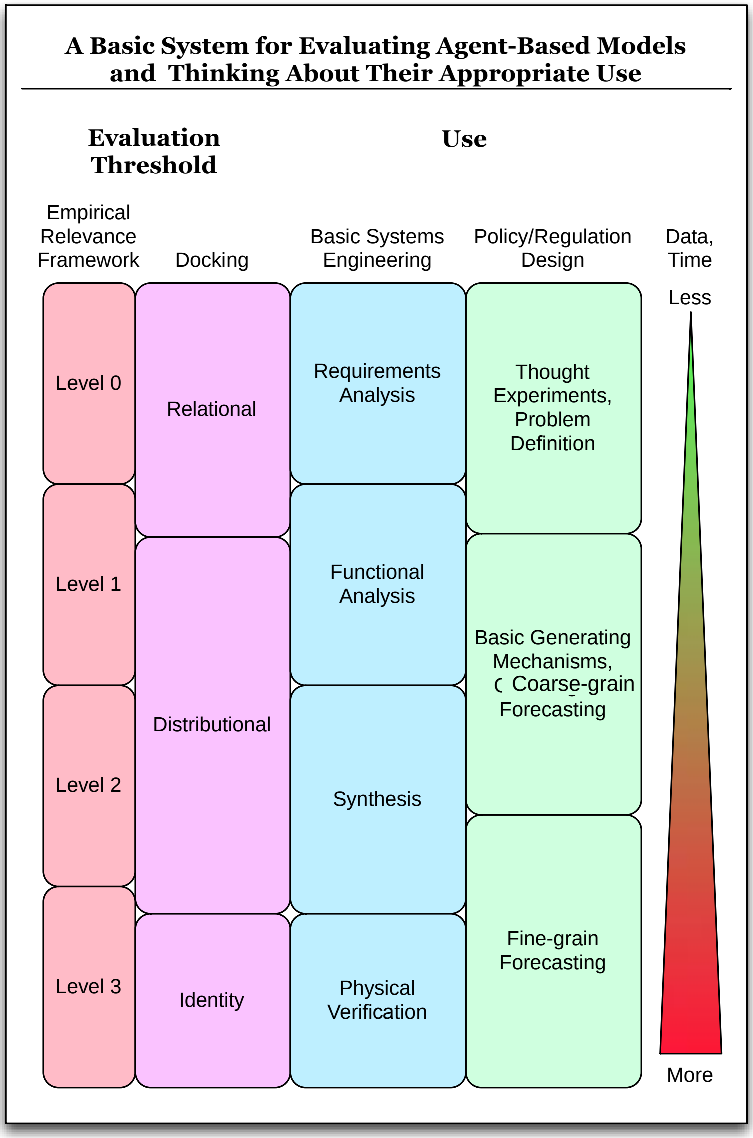

Figure 14. Basic system for evaluating ABMs and their appropriate use.

6.3. Using Agent-Based Models for Forecasting

ABMs are typically used for explanatory models rather than forecasting per se. ABMs demonstrate what conditions suffice to generate a particular outcome, but do not predict when the outcome will happen. For example, an analyst could use an ABM to explore the conditions (armaments, visibility conditions, levels of aggression, communications gear, etc.) under which a U.S. Marine Corps (USMC) fire team could defeat an enemy tank platoon (which has its own set of armaments, aggression, and so on). Running this ABM many times would generate a large number of results that could then be binned by numbers of USMC casualties or by "wins" and "losses." The analyst

would then look for commonalities among runs that fell into the bins of interest. In this example, the ABM helped the analyst to understand a situation of interest, not to identify a situation of interest or forecast that situation's likelihood of occurring. The context for the use of an ABM becomes, "If we find ourselves in situation X, then we can expect these sorts of outcomes." When thinking about outcomes and rates of occurrences or likelihoods, it should be noted that the outcomes of ABMs are often not shaped like a bell curve. This means that traditional notions of likelihood (averages) may not be meaningful and should be carefully considered when used for risk and course of action (COA) analyses.

The fire team offers a fairly simple example, as it involves relatively few agents and they interact in very specific ways. Constructing an ABM becomes significantly more difficult, and the data requirements become more onerous, in more "open" sociocultural realms. However, the time and data requirements can be tempered by increasing the level of abstraction. For example, the 1st Marine Expeditionary Force (1MEF) used an ABM to examine how a population's level of contentment would change as "good" and "bad" events happened in the area of operations (Koehler, Barry, Widdowson, & Forsyth, 2004). Changes in the population's contentment were a function of the group that the population blamed for the events and the population's attitude toward that group, as well as the contentment of the population's social network. This ABM had minimal data requirements, as 1MEF was interested in the dynamics of a relatively generic population; therefore, only the internal mechanisms of attitude change had to be well specified and neither geospatial data nor specific demographic data were needed. This also meant that 1MEF could accomplish the work in weeks, producing a model that was LER Level 0.

The Joint Improvised Explosive Device (IED) Defeat Organization (JIEDDO) has also used ABMs for understanding sociocultural dynamics; however, JIEDDO wanted to understand the impact of these dynamics on IED use (Turnley, Henscheid, Koehler, Mulutzie, & Tivnan, 2012). This meant the ABM had to simulate a specific time and place with a specific population and specific geometry, as well as specific coalition and insurgent concepts of operations. The data requirements and time needed to create the model were both quite high; the effort produced a model that was LER 0–LER 2, depending on the model component. However, JIEDDO could use the model to understand the complex interrelationships among coalition activities, insurgent activities, traditional power networks, and geospatial factors, among others.

7. Hybrid Model Forecasts

A model that combines, for example, system dynamics and ABM approaches can be defined as a hybrid model. According to Prasad & Park (2000), this "approach represents a middle ground between the analog modeling based on differential equations in system dynamics and the discrete rule-based modeling methods common in the agent based simulation community." System dynamics assumes homogeneity of individuals, while ABMs relax aggregation assumptions and can capture individual heterogeneity. However, the complexity of ABMs increases computational requirements; further, ABMs can be difficult to construct and to validate (Rahmandad & Sterman, 2008). ABMs with embedded system dynamics models can overcome some of these difficulties and may provide new insights into the systems modeled (Teose et al., 2011).

7.1. Hybrid Insurgency Dynamics Model

This section uses the hybrid Insurgency Dynamics model to illustrate how such a model can support forecasts. The original model was developed at the Massachusetts Institute of Technology (Choucri, Goldsmith, Madnick, Mistree, Morrison, & Siegel, 2007). The AnyLogic Company (2013) added agents and agent behavior to this model and distributed it as a sample model with their software package. The agent-based portion of the model captures simple agent interaction for recruitment, and is integrated with the system dynamics portion, which captures high-level relationships. We adapted this model further using features from the Counterinsurgency (COIN) model (Turnley et al., 2012) that is based on Epstein's (2002) work on models of civil violence. Updates enabled the agents to belong to social groups and interact with others both within and outside their respective groups. These interactions affect the agent's beliefs and behavior. Next we augmented agents with emotion, specifically characterizing the relationship between anger and contempt and their influence on an agent's tendency toward non-violent and violent direct action (Jost, Chaikalis-Petritsis, Abrams, Sidanius, van der Torn, & Bratt, 2011; Tausch, Beckerm, Spears, Christ, Saab, Singh, & Siddiqui., 2011).

We use groups consisting of agents with similar social characteristics (e.g., ethnicity, political beliefs, and religious beliefs). Initial attributes are based on a group's relationship to other groups (perceived legitimacy, perceived hardship, grievances). Agents interact at variable rates, but interaction among group members occurs at higher rates within groups than across groups. When one agent interacts with another, the model adjusts each agent's activation value (a personal threshold for taking violent/non-violent direct action) based on the other's activation values.

Each agent can be in one of four states: *government supporter, dissident* or protestor, *insurgent* or violent protestor, and *removed insurgent*, as shown on the right of Figure 15. Whether a government supporter becomes a dissident is based on the agent's activation values (i.e., thresholds set). The model calculates initial activation values for each agent at run time based on agent emotions, perceived legitimacy of other agents or groups, perceived hardship, and grievances. An agent in a dissident state may go back to being a non-activist or government supporter after a certain amount of time or when the agent's activation value falls below the threshold. However, an agent that becomes an insurgent cannot go back to the dissident state; the agent remains in the insurgent state until transitioned to the removed insurgent state at which point the agent is removed from the model.

Emotion values, from non-traditional data source Twitter, for anger, contempt, negative emotion, and positive emotion are integrated into the model daily—the model has a daily time step. For example, values for agents within a group (i.e., not individual) are adjusted based on group values and affect their activation state. The model normalizes emotion strength for the number of tweets (ratio of number of tweets reflecting a particular emotion on a given day to the total number of tweets reflecting all the emotions being considered on that same day). For instance, the model adds the value for anger to the agent's activation value as a condition for transitioning from a *government supporter* to a *dissident* state, and adds the contempt value as a condition for transitioning from dissident to insurgent. Other attributes based on traditional data sources include

attitude toward risk, risk aversion, and threshold of willingness to become a peaceful and/or violent activist.

The system dynamics component contains the global parameters for the model, as shown on the left side of Figure 15. Integration points between the system dynamics and agent-based components occur through parameters: propensity to be recruited, number of insurgents, number of dissidents, and number of government supporters. The individual agent state charts shown on the right of Figure 15 incorporate each of these parameters. In summary, the system dynamics parameters are adjusted by tracking the changing population of agents.

7.2. Use Case

Following the 2007 Kenyan presidential election, violence broke out when supporters of the defeated candidate perceived the outcome as unfair. The conflicts exacerbated divisiveness among tribes; thousands of persons were killed and many more displaced from their homes. In 2010, Kenya adopted a new national constitution and in 2012, during the run-up to the next election, two candidates, Uhuru Kenyatta and Raila Odinga, emerged as the frontrunners for elections in 2013. The government and people of Kenya, neighboring nations, and the United States hoped to see non-violent execution of the historical election. We mapped short-term forecasts of dynamic emotion indicators to parameters in a theory-based hybrid model, as described below, to monitor instability that might affect the 2013 Kenyan elections.

7.3. Dynamic Emotion Data

This study used Twitter data to dynamically update model parameters in near-real time, support indicator integration (anger, contempt, positive emotion, and negative emotion), and identified potential threshold values to signal when an analyst should investigate further. To this end, we collected Twitter data sets on Kenyan election-related keywords, hash tags, and usernames between December 2012 and April 2013. The two political coalition-level Twitter data sets focused on Odinga's coalition, the Coalition for Reforms and Democracy (CORD) (for example, #cord, #kalonzo, #odinga, Kalonzo, ODM-Kenya, Wiper) and Kenyatta's coalition, "Jubilee" (for example, #kenyatta, #narc, @williamsruto, Jubilee alliance, Kenyatta, NPK, Ruto, Uhuruto).

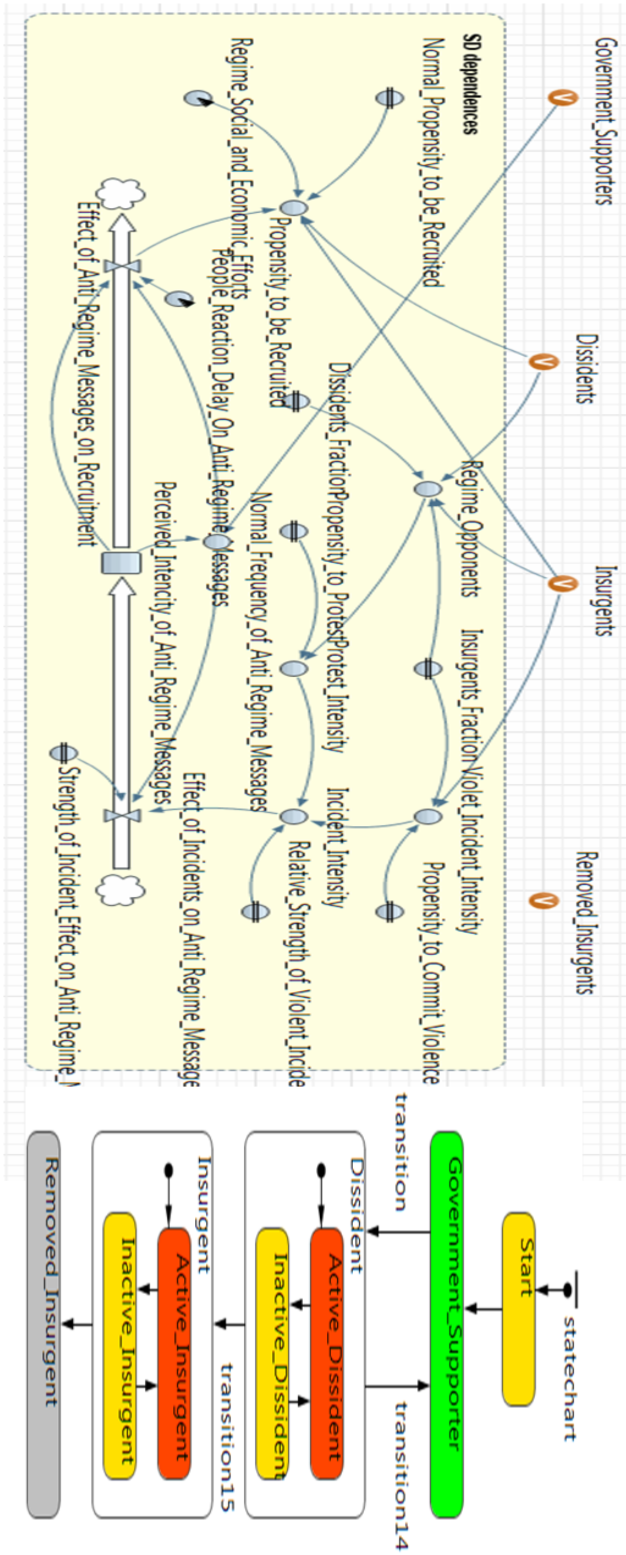

Figure 15. System dynamics and agent-based components integrated through parameters.

The emotion analysis indicators from the LIWC approach (Elson, Yeung, Roshan, Bohandy, & Nader, 2012; Servi & Elson, 2012) enabled the use of dynamic, near-real time data in the model. The LIWC algorithm calculates the ratio of words for one particular category to the total word count for a given set of tweets. The following LIWC emotion indicators from Twitter were integrated into the simulation model based on available social science theory (Figure 16): anger, contempt, positive emotion, and negative emotion. The forecasted values could be constant (averages) or change with time (trends) and are described next.

7.4. Short-Term Forecast of Data

After mapping the near-real time data series to the hybrid model, we needed a short-term forecast of the indicators to evaluate model output. Box and Jenkins (1970) provide techniques for building statistical models with the minimum number of parameters as described below. Their approach involves taking observations at discrete, equally spaced intervals of time and making forecasts for future time intervals. The approach also provides ways to calculate probability limits on either side of the forecasted values, for example, at the ±95% confidence range.

Autoregressive models (ARs) express the current value of a process as a finite, linear combination of previous values of the process and a random value. A first-order AR model uses one point and predicts values using a single coefficient. A second-order AR model of the same data would have two coefficients and use two data points. Moving Average (MA) models take a linear combination of the past residuals to form a prediction. The difference between the prediction and the actual value is called a residual, and the model fit is measured as the variance in the residuals. In a well-fitting model the residuals should be distributed as white noise, i.e., normally distributed with zero mean and a variance.

The AR and MA models can be combined and applied to actual values in the time series data to generate an average forecast or applied to differences in the data values to generate a trend forecast—the latter is called an Autoregressive Integrated Moving Average (ARIMA). The order of the models is described by three values: the number of parameters in the AR, the number of differences, and the order of the MA. We used an ARIMA model with two parameters, one difference, and one order of the moving average. The shaded region on the right of the bottom graphs in Figure 16 show the forecast for the four emotions for the ±95% confidence range.

7.5. Sensitivity Analysis

We performed sensitivity analysis by holding one series of emotion values constant over time while all others were allowed to vary as measured for the Kenyan elections. This process was repeated for a range of values, running each case once. The model parameters and group attributes run in the sensitivity analysis included anger, contempt, probability of arrest, appeasement, removal effectiveness, risk aversion, positive emotion, negative emotion, contact rate, average time as dissident, and desired time to remove insurgents. The number of dissidents was recorded as a function of time.

During the sensitivity analysis, we observed thresholds of emotion in which the number of dissidents increased or decreased. For example, increased anger (values tested 0.001-0.009) in the

CORD dataset did not correspond to an increase in the number of dissidents in the model; however, in the Jubilee dataset the number of dissidents rose as anger rose. Specifically, after April 10, 2013 the number of CORD dissidents decreased to zero for all values of anger, but for a constant value of anger greater than 0.003 the number of Jubilee dissidents increased, as shown in the top of Figure 16. This revealed that the Jubilee data set is more sensitive to anger—it did not decrease to zero. In summary, using the highest anger value tested (0.009) in the model was not enough to create CORD dissidents but values greater than 0.003 anger created dissidents in the Jubilee dataset. The reason this happens is due both to the emotions in the datasets (CORD vs. Jubilee) and model structure. Positive and negative emotion contributes to an agent's propensity to be recruited, which impacts an agent's threshold for becoming a dissident. Therefore, in the CORD dataset, the values for positive and negative emotion offset the anger response. Similar thresholds can be extracted from the positive and negative emotion results; however, the contempt words were not evident in these data sets, as illustrated in the bottom of Figure 16.

7.6. Conclusions

Fortunately, the 2013 Kenyan elections proved largely peaceful. Actual US courses of action (COAs) included Department of State messages and President Obama's video message in February 2013 wishing Kenyans a peaceful election. The two data sets showed little correlation between these messages and the LIWC emotions, because the data sets focused on immediate party politics and leaders.

This study used Twitter data to dynamically update model parameters in near-real time to support indicator integration (anger, contempt, positive emotion, and negative emotion) to determine potential threshold values to signal that an analyst should investigate further. Using a theory-based model with short-term forecasts of the emotion indicators to determine the degree of emotion necessary to trigger an increasing number of dissidents is our contribution and requires further work. Other future work should include calibrating the potential COAs for the amount of change necessary to counter the trend in the number of dissidents. The largest research gaps include instantiating social science theory in simulation models including identifying other theories to test; obtaining robust, meaningful, dynamic datasets to update theory-based models; and determining how best to use the data in the modeling process.

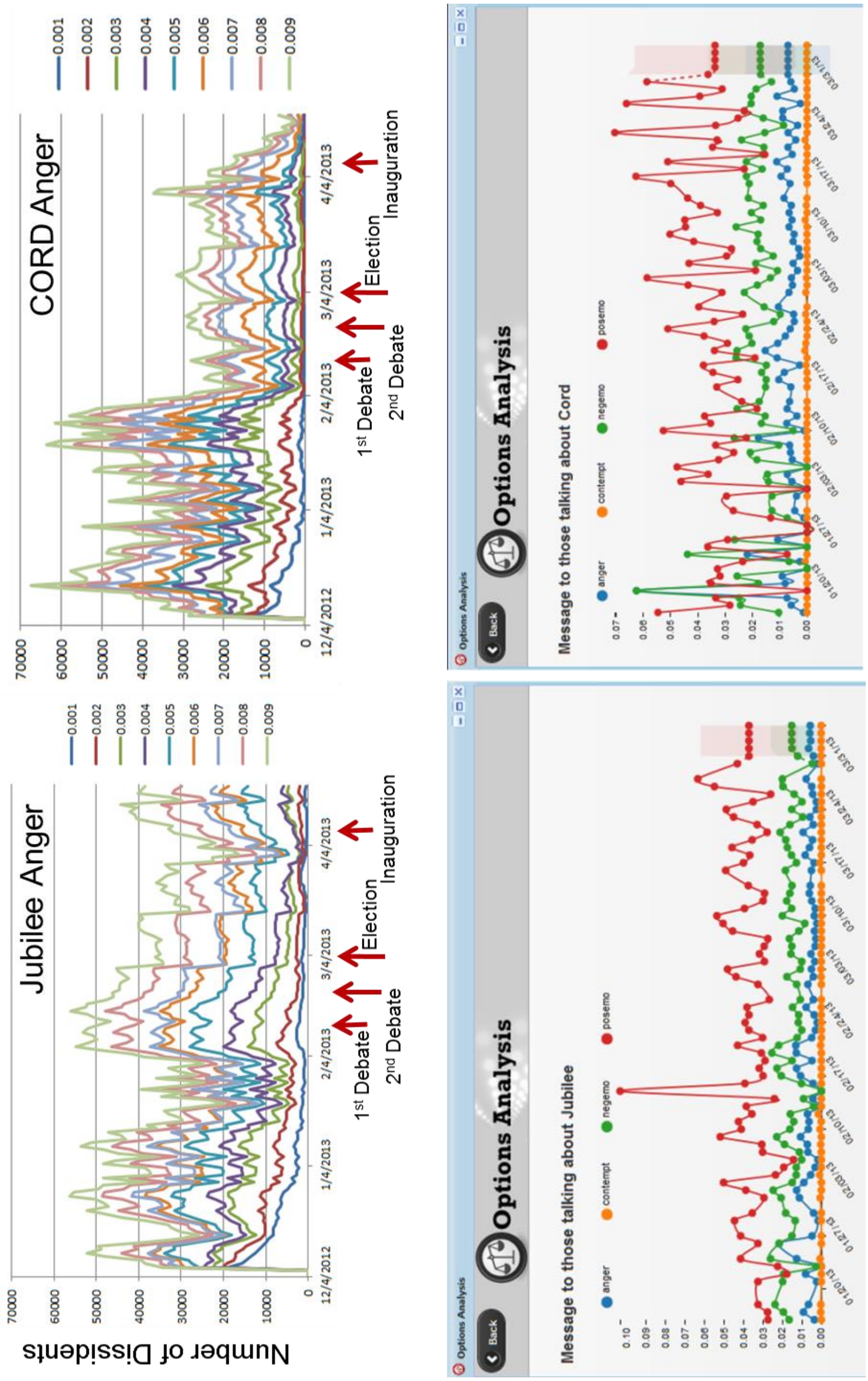

Figure 16. LIWC indicators over time with a 5-day short-term forecast (bottom) and sensitivity analysis to determine thresholds for emotion indicators (top).

8. Evolving Self-Organizing Maps (ESOM)

Self-Organizing Maps (SOM) is a soft-computational technique for visualizing high-dimensional data (Kohonen, 2001). According to McGaugh (2012), SOM addresses flexibility issues by processing data iteratively to enable the best mathematical representation of data while preserving the underlying structure of the data. Complex systems can be analyzed and modeled using SOM since it uses unsupervised learning algorithms thereby allowing clustering of the data without requiring the modeler to know the class membership function of the input data (Simula, Vesanto, Alhoniemi, & Hollmén, 1999). Deng and Kasabov (2000) proposed an algorithm of Evolving Self Organizing Map (ESOM) in which one passes learning on in the dynamic version of the Kohonen SOM. SOM evolves over time, adapting itself to changing data streams by providing a method for good clustering, data analysis, visualization, and prediction. This algorithm can be extended for supervised learning by augmenting input vectors with target output variables during the training session. The output value of the best matching unit (BMU) of the trained model is then substituted for the predicted value for the input vector without augmentation for which prediction has to be made (Deng & Kasabov, 2000).

Among the SOM algorithms investigated, ESOM yielded the most promising results. ESOM starts with the model set to zero output nodes. As an *n*-dimensional input vector is presented to the model, the algorithm determines the Euclidian distance from all the existing output nodes. If no output node exists (the condition when the first input is received for training), the algorithm creates a new output node in the image of the current input nodes. Thus the output nodes have the same dimensions as the input vector. If the smallest distance between the current input vector and output nodes is greater than threshold value ε the algorithm creates a new output node in the image of the current input vector. If the smallest Euclidean distance between the current input vector and output nodes less or equal to ε, the output node that has the minimum distance from the current input vector is called the Best Matching Unit (BMU). The algorithm updates the location of the BMU resulting in it becoming closer to the current input vector. Additionally, it updates the two closest neighbors of the BMU.

After presenting all input vectors and the training phase terminates, the ESOM model can be used for testing and prediction. ESOM can be applied to supervised learning tasks such as classification and prediction as described by Deng and Kasabov (2000). Results from the study of Afghanistan (Ahram & Karwowski, 2012) showed that ESOM can help to forecast adverse events by drawing on knowledge of selected socioeconomic factors as well as information about the recent adverse events that occurred in a given region.

8.1. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are mathematical models of the human brain that can identify complex nonlinear and dynamic relationships between input and output datasets. According to Choubey, Sehgal, and Tandon (2006), the Multilayer Perceptron (MLP) is the neural network model type most commonly described in the literature. An MLP is a type of supervised network as it needs a desired output in order to learn. This type of network uses historical input and output to build a model that correctly maps the future real data to the appropriate output.

According to Assi, Shamisi, and Hejase (2012), a graphical representation of an MLP has three types of layers: input layer, hidden layer, and output layer, as shown in Figure 17. Neurons in the input layer distribute the input signals to neurons in the hidden layer. Each neuron in the hidden layer sums up its input signals after assigning them the weights of the respective connections from the input layer. This weighted average is then applied to a simple threshold function, sigmoidal function, hyperbolic tangent function, or radial basis function to obtain the output. The back propagation algorithm is the most commonly adopted MLP training algorithm. It changes the weight of the connection between each pair of neurons (Assi et al., 2012) based on the desired learning rate and the difference between the target output and the actual output as shown in Figure 18.

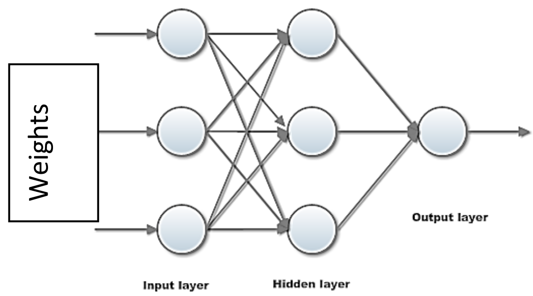

Figure 17. Architecture of a multilayered neural network (adapted with permission from Dayhoff & DeLeo, 2001).

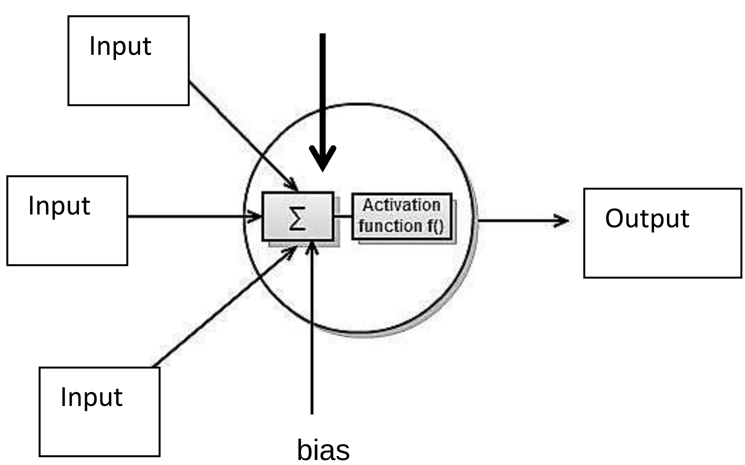

Figure 18. Typical artificial neuron (adapted with permission from Dayhoff & DeLeo, 2001).

8.2. Afghanistan Study

The Ahram and Karwowski (2012) study of Afghanistan used these soft modeling methods to generate forecasts that would guide allocation of development funds for stabilizing regions with high levels of adverse events and to better understand the complex socioeconomic interactions caused by adverse events. The Department of Defense's Human Social Culture Behavior (HSCB) Modeling program provided two different types of datasets collected between 2002 and 2010. The study used a set of spatial data representing social and economic factors from *Worldwide Incidents Tracking System* Geography (WITS GEO), the U.S. Agency for International Development (USAID), and AISCS (African Immigrants Social & Cultural Services). The adverse event dataset included information regarding the date of an event; incident type; number of people killed, wounded, and kidnapped; province, city, and district; description of the event, and simple event summary. The infrastructure aid dataset included the urban and rural population density, province, city, district, country, project types, allocated budget information for different sectors, amount of aids in each sector, types of construction, and usage of airfields. The model outputs included adverse events in terms of the number of people killed, wounded, hijacked, and total number of adverse events.

The study divided Afghanistan into seven regions for analysis purposes. For each model, the data from 2002–2009 were grouped and used for training, while the 2010 data were used for testing. The researchers investigated the performance of each of the 96 models using the Mean Absolute Error (MAE) and the prediction accuracy within ±1 error range (difference between actual and predicted value). The sensitivity analysis showed the importance of the relationship between the varied economic development projects on geographical regions, population density, and occurrence of adverse events in Afghanistan.

9. Forecasts of Social Networks Generated from Text Analysis

For research questions that involve dynamics, such as explaining how networks emerge, how information diffuses through networks, how a community's beliefs change as a function of network changes, or how networks evolve, computer simulation is generally used. Most of these social network simulation models are aimed at understanding or predicting the spread of information, beliefs, goods, or diseases through networks. As such most of the models take into account some measure of network exposure – the likelihood that an actor will be exposed to something because of the number of others that they are linked to who already have been exposed. Most such models take into account social influence, i.e., the extent to which an actor is likely to behave in a certain way or hold a certain belief, because others to which that actor already is linked behave in that way or hold that belief. Consequently, most such models also have a way of predicting cascades, i.e., the trace of change in who knows or has what as a function of an initial exchange.

Agent-based simulation is considered a natural for simulating networks. In an agent-based model, social behavior emerges from the actions of and interactions among the individual simulated actors, i.e., the agents. In most agent-based models, all agents are of one type, e.g., all people or all organizations, and the activity often does not take into account actual social network constraints,

use of communication technology or the role of media including social media, or geographic issues. Social networks are often inferred by which other agents an agent comes into contact with based on their position in a grid. Such grid based networks are not similar to natural human social networks in that they tend not to have appropriate distributions of strong and weak ties, degree centrality and reciprocity.

In contrast, to traditional agent-based models, agent-based dynamic-network models use or generate networks that are more socially realistic. In an agent-based dynamic-network model, the agents are not located in grids but in networks. Moreover, these networks may evolve over time; i.e., who is connected to whom and the strength of such connections may change. An example of such an agent-based dynamic-network model is CONSTRUCT.

CONSTRUCT is an agent-based dynamic-network simulation framework that can aid assessments of changes in the distribution of knowledge and sentiment at the social level (Carley, Martin, & Hirshman, 2009). It is an extension beyond the standard ABMs previously described. Based on the constructural theory of sociocultural structuration (Carley, 1990), the CONSTRUCT model supports reasoning about the social network and learning dynamics that underlie the diffusion of information and dispersion of beliefs as the networks evolve. CONSTRUCT is the first agent-based model in which the agents are distributed in high-dimensional social and homophily networks, such that the networks need not be static but instead co-evolve with the knowledge networks. The model has been validated in numerous settings including predicting the impact of inter-marriage, leadership, and change in terror groups (Schreiber & Carley, 2004).

9.1. Basic Constructural Model

CONSTRUCT takes as input the initial observed social, knowledge and belief networks, as well as communication media. Input can also include other homophily characteristics in terms of socio-demographic characteristics of the population. The social network defines who interacts with whom, the knowledge network (who knows what), and the belief network (who believes what). Agents have a "transactive" memory of other agents; thus, each agent has a perception of what others know and believe and with whom they are likely to interact. Agents can communicate those perceptions – and those perceptions can be wrong.

CONSTRUCT can be instantiated using data on either real or hypothetical groups, and therefore using real or artificial data. To gather real data, as was done in Carnegie Mellon University's "SUDAN Game" (Landwehr, Sparagen, Ranganathan, Carley, & Zyda, 2012), researchers can mine the text of news or social media to extract the set of actors, topics (often characterized as knowledge), beliefs, and the relations among them. Those data function as time "0" data; i.e., the starting case. CONSTRUCT then simulates the system and "updates" the data to show how they may look at time "*N*"; i.e., at some later date. To facilitate instantiation of the CONSTRUCT model, analysis of the results, and validation of the results against real data, CONSTRUCT interoperates with other tools, such as AutoMap, a text mining tool that extracts networks in DyNetML, and ORA, a network analysis tool that reads and writes DyNetML. Finally, ORA can process and analyze the CONSTRUCT results and compare them with other data in the same format.

While the networks view the homophily characteristics as unchanging, at least in the short run, they have the potential to evolve. This evolution is a function of the communication-learning cycle that all agents undergo more or less simultaneously. This means that two agents will have a number of characteristics in common – e.g., age and gender – that will persist over time, and may also share certain information or beliefs. As these agents interact they will learn new information, learn what others believe, and therefore change what they know and possibly believe. Thus the similarity of these agents in knowledge and beliefs may change.

Whether or not two agents interact is a function of their position in the social network and the available communication media. Agents are more likely to interact with those to whom they have strong social ties. However, they occasionally interact with those to whom they are weakly tied. Depending on the communication media available, these interactions occur simultaneously or asynchronously. For example, agents with access to email can send a message to multiple other agents simultaneously, but the other receivers may receive that message at different times. By contrast, in a face-to-face interaction both agents must be co-present and two agents participate, unless it is a group meeting.

The social network used for interaction is the underlying "true" social network, defined as a distribution of interaction probabilities. These probabilities depend on any or all of the following: how much information the two individuals share; how similar the two individuals are in their beliefs; how much information the one individual thinks the other has, i.e., called "ego"; similarity in socio-demographics; and organizational or physical constraints on the need to interact or that prevent interaction. In general, each of these factors is defined relative to the individual's similarity or difference with all other actors including his or herself. These factors are used to construct the relative similarity between two individuals, taking into account the observed network, shared knowledge and beliefs, and socio-demographic similarities. This relative similarity is treated as an interaction probability.

When agents interact, they communicate. The complexity, and to some extent the content, of those communications vary based on the communication media; for example, Twitter messages are less complex than books or phone calls. As agents interact and communicate they learn the new information or beliefs, with possible error and with forgetting. At each time step the model updates the probability of interaction between each pair of agents based on the evolving set of information and beliefs. Thus, in the long run, and with sufficiently large enough bodies of knowledge and beliefs, whether or not two agents interact will become more a function of the learned information than of the initial observed network and demographic properties. However, in the short run, the existing structure and the socio-demographics dominate.

Learning has a key impact on the agents: it changes which other agents they are likely to interact with in the future and what they can communicate. In this sense, the social, knowledge, and belief networks in CONSTRUCT co-evolve. As agents communicate, learn, and change their positions in their social networks, groups can emerge and disappear, culture can shift, and individual agents can increase or decrease in prominence.

9.2. Illustrative Results

Consider the following three examples: winning hearts and minds, resilience to cyber attack, and targeting impact. In the first case, winning hearts and minds, analysts used CONSTRUCT to assess a diffusion question: specifically, how to best communicate with a population to influence overall sentiment toward the United States (Louie & Carley, 2008). The analysts ran a virtual experiment that considered messages via different media at different frequencies, with messages coming from both friendly and adversarial agents. The study compared three modes of communication: having a single speaker tour the area giving talks, publishing articles in a newspaper, and posting articles on the web. Figure 19 shows the result of this experiment. Although negative sentiment toward the United States persisted, the greatest mitigation resulted from providing information on the web, even when literacy is low, thanks to the high level of access and the ease of forwarding the material.

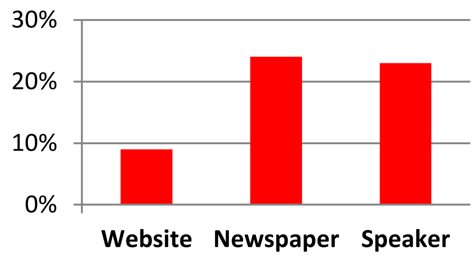

Figure 19. Winning the hearts and minds.

In the second case, analysts used CONSTRUCT to assess a cyber security question: specifically, whether coordination and data sharing between combatant commands makes them more resilient to cyber attacks (Lanham, Morgan, & Carley, 2011). This involved a virtual experiment for two scenarios. In the first case, the commands did not share data; in the second case, they shared data. Figure 20 shows that data sharing actually made the commands less resilient in the face of reliability attacks and more resilient to integrity attacks due to the implicit “backup and propagation” of viruses and good, non-corrupted information, respectively.

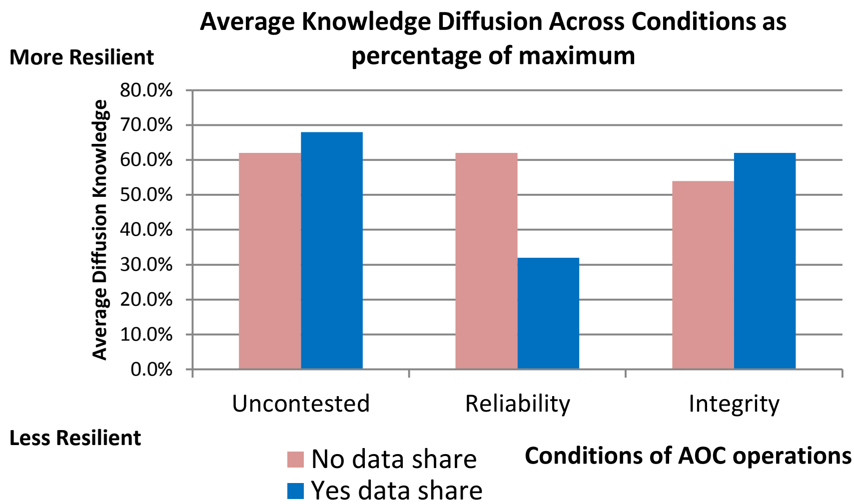

Figure 20. Resilience to cyber attack.

In the third example, analysts used CONSTRUCT for COA assessment. The specific example comes from targeting, asking whether the expected performance of a covert group degrades if the key leader is removed (Carley, Dombroski, Tsvetovat, Reminga, & Kamneva, 2003). As shown in Figure 21, removal of the leader degrades the performance of this particular group; however, this result depends strongly on the network structure.

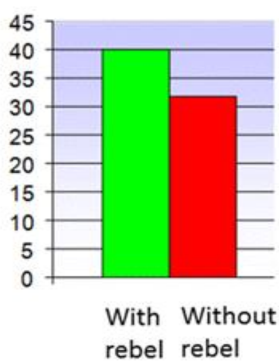

Figure 21. Targeting impact.

9.3. Overarching Comments on CONSTRUCT

CONSTRUCT is a powerful agent-based dynamic-network simulation engine. It can be instantiated using actual or theoretical networks. With CONSTRUCT, a number of questions can be addressed concerning the impact of various interventions in the social-cyber domain. Questions about the

diffusion of ideas, change in sentiment, and related changes in activities under diverse sociocultural and media scenarios can be addressed.

CONSTRUCT is illustrative of the type of model in which the social network constrains and enables individual behavior. It is distinct from most agent-based models as most such models either do not consider the social network, or treat the social network as fixed. It is distinct from the generative models as its focus is to explain the evolution of real social behavior, not to provide a mathematical description of the emergence of a network form based on simple principles.

A key limitation is that knowledge is represented as a binary string and the amount of knowledge per actor can be difficult to estimate. A second limitation is that the time required to instantiate a new model, particularly when there are many courses of action to estimate, can be substantial.

As we look to the future, several advances with CONSTRUCT are underway. First, CONSTRUCT is being made interoperable with ORA so that the analyst can automatically generate an input deck for CONSTRUCT using the network data as input. This facilitates re-use. Second, additional types of media are being added so that CONSTRUCT can be used to explore how best to communicate with populations to effect changes in beliefs using social media.

Finally, a key value of CONSTRUCT, unlike other agent-based models of information diffusion and belief dispersion, is that CONSTRUCT takes into account the social network and allows it to co-evolve with the culture over time. As such, CONSTRUCT is valuable for general prediction of change in atmospherics. The movement to enable CONSTRUCT to be auto-instantiated from any network data in CONSTRUCT will greatly ease the analyst's ability to do predictive forecasting.

10. Judgmental Forecasting

Decision makers in many fields rely on predictive systems to inform their judgments and planning activities. Many of these systems involve statistical models or algorithms to derive forecasts from relevant data sources (Box, Jenkins, & Reinsel, 2008). Examples include many econometric models, such as those used to forecast unemployment rates or consumer price values (Makridakis, Wheelwright, & Hyndman, 1997). In other cases, statistical models may produce inputs to inform a forecast, with a human expert adjusting the prediction based on exogenous factors. For example, Silver (2012) has recently demonstrated methods for identifying and pooling information from multiple data sources to produce forecasts.

In cases where no robust statistical models or data streams are readily available, policy makers frequently turn to the judgmental forecasts offered by individual experts. However, a growing body of research indicates that the predictions of individual subject matter experts tend to have limited accuracy, often failing to exceed the accuracy of non-expert judges or simple algorithms (Sanders & Manrodt, 2003; Tetlock, 2006). Fortunately, researchers are now actively developing methods for combining multiple expert judgments, and these methods show considerable promise for remedying the weaknesses of expert forecasts (e.g., Abramowicz, 2007; Surowiecki, 2004). This section describes issues and advances in this emerging field of aggregative judgmental forecasting.

The methodological challenges for using expert judgments from multiple forecasters include identifying forecasters to survey, determining reliable criteria for identifying good forecasters, and finding the best ways to elicit information from the experts. Thereafter, automated methods must merge or aggregate the judgments provided by multiple forecasters to produce a “best” overall forecast and communicate the results to the decision maker.

To illustrate these concepts, consider the following forecasting problem posed at the end of 2011: “Will €1 Euro buy less than $1.20 U.S. dollars at any point before 1 January 2013?” During the last quarter of 2012, the Euro was trading at about $1.30, with some fluctuations (Figure 22). The European debt crisis, including the poor financial health of countries such as Greece, raised serious concerns about the value of the Euro.

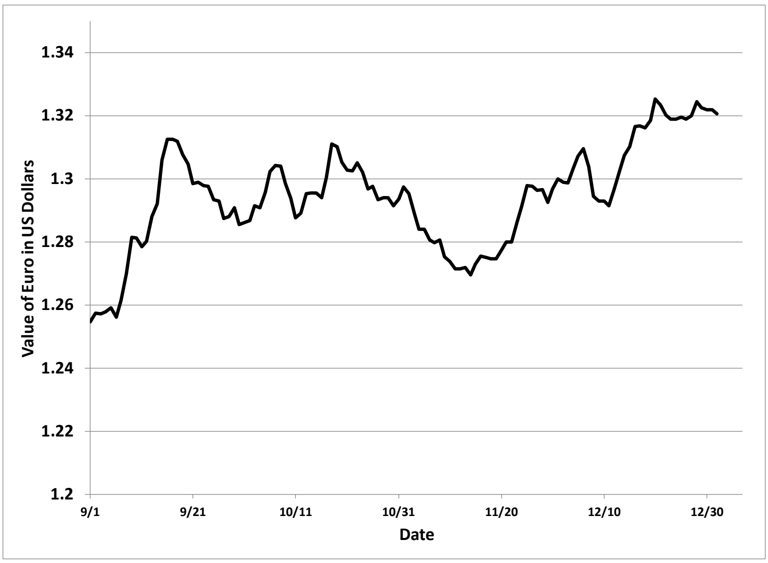

Figure 22. Daily value of the Euro in U.S. dollars in late 2012. Adapted with permission from OANDA (2013).

A pool of forecasters provided judgments for this problem. Responses from these participants were collected via a web-based interface in which each respondent answered a small number of questions, including an assessment about whether the event would happen (Yes or No), a probability assessment of the likelihood of the event, and a few questions about self-assessment of expertise and access to knowledge about the forecasting problem. Researchers have long understood that aggregate estimates built from the individual opinions of a large group of people often outperform the estimates of individual experts (Surowiecki, 2004). Therefore, this research used a simple method for aggregating the individual forecasts: the average of the probability forecasts, also known as the unweighted linear opinion pool (UlinOP). Figure 23 shows the UlinOP for the Euro value forecasting problem.

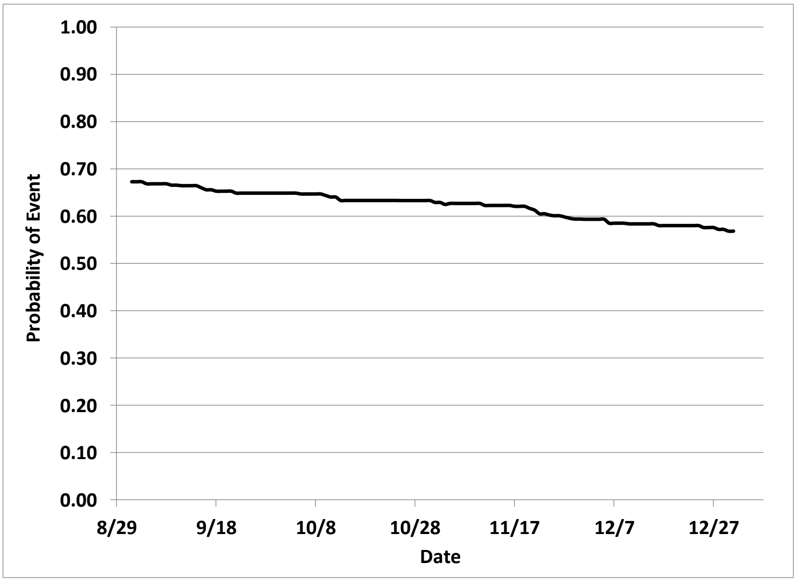

Figure 23. Un-weighted linear opinion pool for the Euro problem. Adapted with permission from OANDA (2013).

Given the volatility of the value of the Euro, early in the life of this forecasting problem researchers might have expected the value to dip below $1.20. However, as the end date approached the prospect seemed much less likely. The UlinOP responded slowly to the approaching deadline, primarily because it weighted all opinions equally, including the less informed ones.

Improving this situation poses a major challenge for judgmental forecasting. One promising variation is the prediction market (Graefe & Armstrong, 2011), which accepts trades or bets on accounts (using actual or "play" currency), and in so doing incentivizes participants to update their forecasts, particularly when a deadline is approaching. Evidence suggests that prediction markets, especially using the newest techniques, are at least as accurate as other institutions predicting the same events with a similar pool of participants (Berea, Maxwell, & Twardy, 2012; Nagar & Malone, 2012).

10.1. Identifying Good Forecasters

Common sense would suggest that relevant subject area knowledge would lead to improved forecasting performance. Recent studies have shown that forecasters who correctly answer knowledge-based questions related to the problem perform only slightly better than persons with less knowledge (Miller, Forlines, & Regan, 2012; Miller, Kirlik, & Hendren, 2011). One approach to identifying good forecasters is to explore psychological factors, such as education, demographics, and various measures of aptitude and personality. Several studies have found a small but consistent benefit from certain personality traits (Poore, Regan, Miller, Forlines, & Irvine, 2012; Ungar, Mellers, Satopää, Tetlock, & Baron, 2012). Retrospective analysis reported by Poore et al. (2012) reveals performance distinctions resulting from personality, deductive and inductive

approaches to problem solving, and different motivations for problem solving. By selecting forecasters with the appropriate aptitude and personality traits, researchers can realize a small but statistically significant boost in performance.

10.2. Aggregation of Results

Developing better methods of aggregating the individual forecasts to achieve greater accuracy presents an interesting challenge (Rantilla & Budescu, 1999). Recent research has shown that combining judgments through averaging leads to poor prediction performance, as illustrated above. One intuitive approach is to assign greater weight to predictions made by "experts," but, as noted, identifying the experts among the pool of forecasters is not easy. Ways to address this problem include eliciting additional information to assess each forecaster's expertise, sharing information in a way that increases expertise among the forecasters, and training forecasters in skills that enhance performance.

To illustrate the effects of various factors on the accuracy of the forecast, we return to the Euro example. Recall that the event did not occur, so lower probabilities are more accurate. As we saw earlier, the simple average or UlinOP does not perform very well. A simple procedure that assigns greater weight to the most recent forecasts, with some smoothing, shows better performance as the end date approaches. Forecasters who make their prediction closer to the end date have the advantage of more current information and, consequently, provide better forecasts.

When participants in the forecasting pool can update their forecasts, a news report indicating a change in conditions related to the forecasting problem may trigger adjustments. In Forlines et al. (2012), relatively few participants actually provided updates. A heuristic aggregation procedure weighted the respondents by update frequency, propensity to make estimates at the top or bottom of the probability range, and access to knowledge. If the number of updates to the forecast functions as a surrogate for the respondent's level of interest or engagement, forecasters who update frequently are likely to be more accurate. Furthermore, updating means that the latest forecast is presumably based on the latest information. The probability estimate can be seen as an indication of confidence, so greater weight was given to more extreme probability estimates, i.e., values closer to zero or one. Questions about access to knowledge yield an implicit self-assessment of the respondent's expertise. The study weighted the individual forecasts by these three factors and combined them to produce the heuristic forecast depicted in Figure 24. This aggregation scheme dramatically outperformed the UlinOP in this case, although some volatility is evident early on. This technique has also performed well on a number of other forecasting problems, although it has failed as well (Forlines, Miller, Prakash, & Irvine, 2012).

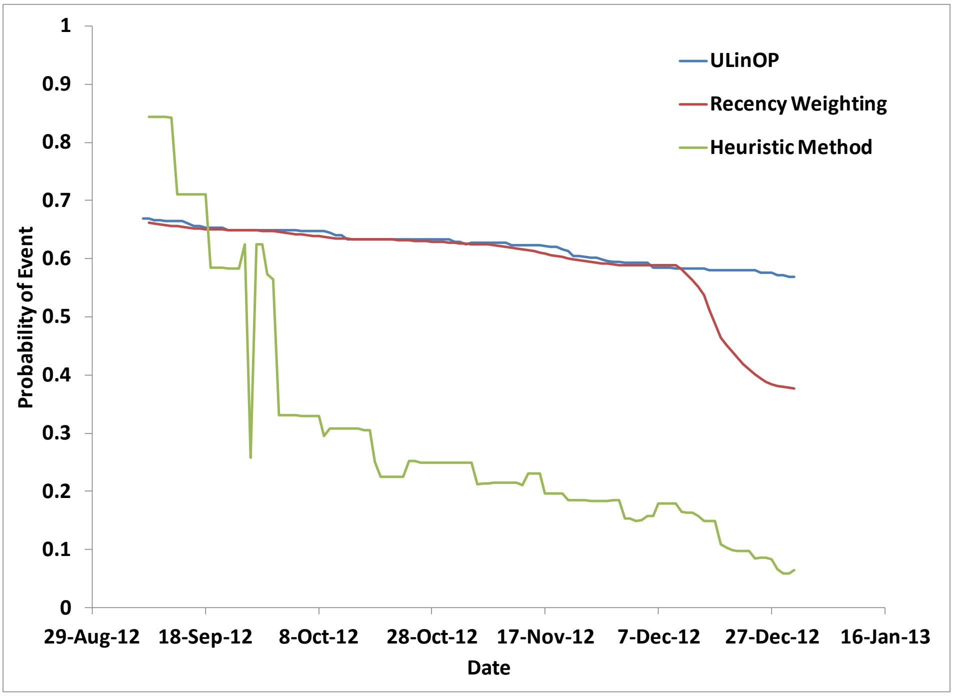

Figure 24. Comparison of selected aggregation methods. Adapted with permission from Forlines et al. (2012).

Current research is developing new aggregation methods that may well outperform the simple average in most cases. In addition, active research explores ways to identify the best forecasters (Prelec, Seung, & McCoy, 2012) and to improve methods for aggregating the information (Irvine, Srinivasamurthy, Regan, & Prelec, 2012).

10.3. Lessons Learned and New Directions

Realizing good performance from judgmental forecasts poses many challenges (Lawrence, Goodwin, O'Connor, & Önkald, 2006; Tetlock, 2006). In many cases, seemingly less qualified individuals can perform almost as well as experts by conducting a moderate amount of research. Some important lessons from recent studies show that training can help forecasters think more clearly about the forecasting problem, and that on average trained forecasters perform better (Ungar et al., 2012). Good elicitation techniques can also improve forecasting performance (Deloatch, Marmarchi, & Kirlik, 2013; Marmarchi, Deloatch, & Kirlik, 2013; Miller et al., 2011; Tsai, Miller, & Kirlik, 2011). Aggregation of expert judgments outperforms individual forecasts (Graefe & Armstrong, 2011), and several methods outperform the UlinOP under a wide range of conditions (Forlines et al., 2012; Irvine et al., 2012; Ungar et al., 2012; Miller, Forlines & Irvine, 2013).

One potential avenue for improving forecasts involves the development of better hybrid methods that combine the best elements of model-based (statistical) forecasts with expert judgment.

Returning to the forecasting problem related to the Euro exchange rate, the underlying data are amenable to statistical modeling. The autocorrelation function, which measures the correlation between observations separated by a fixed difference in time, is high for small differences in time and tapers off as the time interval increases. Thus, a statistical model that predicts future values based on the current value and the recent past will probably perform well over a short period, but become progressively less accurate over a longer time horizon. Some researchers (e.g., Nagar & Malone, 2011) have already begun to explore the potential of human-model hybrids that use a weighted combination of model-based forecasts and expert judgments, where the weights depend on the time horizon.

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11 Making sense of Social Radar: V-SAFT as an intelligent machine[1]

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1. Introduction

"Social radar" is a metaphor: in other words, a model. A model projects something known about a "source" onto something less well known—a target. We see the moon (the target) differently when we hear the metaphor: "The moon is a ghostly galleon." In effect, the poet asks the reader to use "ghostly galleon" as a model for the moon. How we visualize the moon when we use that model results from our individual expectations, emotions, and images associated with the idea of a "ghostly galleon." Under the influence of the metaphor, i.e., when employing "ghostly galleon" as a model for the moon, we see the moon not as an astronomical object but as a spooky vision, floating silently, mysteriously, perhaps ominously, through the clouded darkness.[2] Taking "social radar" seriously as a metaphor, and therefore as a model, can illuminate many aspects of this vision for forecasting.

2. Objective

Radar detects and tracks objects in the sky by sending signals that bounce back in decipherable patterns to reveal the position, size, direction, and velocity of air- or spaceborne objects. Sonar signals reflected from the rocks, canyons, and other formations on the ocean bottom depict an entire landscape of shapes, with fish or ships discernible by their shape and especially their movement. Actively and systematically interrogating the social environment for "bounce-back" signals about occurrences represents a simple analogy with straightforward implications.

Because the laws of physics are fairly well understood, projecting the path of objects whose signature has been detected via radar or sonar is rather straight-forward, at least when it comes to assessing probable immediate trajectories. But the dynamics of the social realm are much more complex than those normally faced by radar engineers. Moreover our theories of "social physics" are much weaker. To some extent, extrapolation of present trends is possible and useful, enabling an uncomplicated analogy between tracking and extrapolating the path of a moving object and

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[2] For detailed consideration of the warrants for and limits to thinking of models as metaphors and vice versa see Weisberg (2013).

tracking and extrapolating patterns of human sentiment or behavior (Maybury, 2010). But forecasting probabilities for most kinds of political, social, cultural, and economic events of interest for policy makers and analysts requires much more than extrapolation. Thinking deeply about “social radar” as a metaphor and therefore as a model can help us appreciate the challenge of forecasting in the human social, cultural, and behavioral sphere, and guide us toward appropriate strategies for addressing that challenge. The main problem is that the future, by definition, does not exist, so signals, or questions addressed to it cannot be reflected back, or answered. There is simply nothing “there” to reflect our signals or to form the basis of an answer to our queries.

To make sense of “social radar” as a model for investigating the future, i.e., for forecasting, we must do three things: (1) produce a surrogate for the future that can serve as the “target”, (2) develop techniques for interrogating that target—signals we direct toward it in the form of queries that return analyzable patterns of information, and (3) design and implement visualizations to transform, filter, and present data in accessible and interactive forms.

3. Approach

One way to produce a target of something that does not exist—such as the future—is to virtualize it. The well-known and well-established technique of scenario analysis rests on this understanding. Instead of loosely pondering the vast number of discrete events that could occur, an analyst or group of analysts devises a small set of stories about how the present might evolve toward the future with respect to a particular issue area or a particular outcome by following an imagined “punctuation” of prevailing trends. This technique creates surrogate futures as objects of analysis. These scenarios are “virtual” in that they exist, or at least are translated from, images in the minds of their producers. Such translation involves an arduous process.

The future has at least as many dimensions as the present. “Transition rules” (i.e., the laws of social behavior at all levels of analysis) are unknown, or at least only partially understood. Hence, every story about what the future may hold must include large doses of arbitrary, even idiosyncratic, decisions about what dimensions and variables will dominate, in what combinations, in what sequence, and with what consequences. This reality turns scenario production into more of an art than a science, posing difficult challenges for traditional techniques of scenario production for the shaping of the surrogate future to be interrogated. In particular, four factors play crucial, non-scientifically justified roles in typical processes of scenario production: (1) employment of seductive but highly arbitrary “black swan” details, (2) a vast array of human heuristics or “psychologics” that tend to trump scientifically based inferences, (3) standard procedures for the entertainment of three options (two extremes and a “mixed” or “intermediate” version), and (4) political biases or political influences on the analytic process.

If we cannot rely on our imagination to produce scenarios as a suitable surrogate for the future, toward what are we to point our “social radar” for forecasting purposes? After all, to make sensible the metaphor/model of “social radar” directed at the future, we must direct our questions (the outgoing radar signals) toward a target. The real target is the future, but the future, by definition, does not (yet) exist. Accordingly, we need a surrogate for the future as a target for our “social

radar" signals. Our forecasts can be no better than the surrogate we use for the way the future could emerge. As noted, a short list of BOGSAT ("Bunch of Guys Sitting Around Talking")-generated scenarios is clearly inadequate. The target toward which forecast-oriented "social radar" directs its queries must instead be produced in a logically consistent, theoretically coherent, and empirically supportable manner. Instead of bouncing our "signals" off a small number of idiosyncratic and perhaps wholly impossible scenarios, we must imagine the future as a high-dimensional space of possibilities. The bounce-back we receive from this space in response to our queries will then enable a mapping not of the actual future, but of the shapes and contours of that space of possibilities.

Let us take a closer look at the distinction between the "actual" future and the space of possible futures. From any time labeled the "present," we can only imagine or visualize the "future" correctly as a large set of multidimensional trajectories. These trajectories trace through an enormous, but not boundless or totally disorganized, "state space" of the possible worlds that could evolve from the world that we experience as the present. In other words, looking forward from the present, we can imagine many ways, along many dimensions, some important and some not, in which the actual set of events of our world can vary.

Most traditional approaches to forecasting seek to anticipate an "actual" future or its probability, at least along some specific dimension. Implicit in the view that we could predict the trajectory of the actual future in some detail is either a faith-based belief in prophecy or an utterly mistaken assessment of the power, coherence, and comprehensiveness of available social theory. To make matters worse, a salient but, in any particular case, unanticipatable fraction of the explanation of what actually happens will emanate from causes located below the analytic horizon of any of our theories.

With these considerations in mind, we must instead understand the process of forecasting political events of interest (EOIs) in a particular setting as an exercise in tracing the contours of the space of possible futures, along relevant dimensions, rather than searching for the one actual trajectory that our world will follow through that space. "Point predictions" are fool's gold. For complex social problems systematic analysis cannot produce them and attempts to do so encourage a fundamentally misleading construction of the problem. What we can achieve are informed judgments about probabilities and associations within distributions of outcomes. Figure 1 highlights the irrationality of seeking to predict the actual future by locating that future as a nearly imperceptible dot in a schematic depiction of intersecting spaces of the conceivable, the possible, the plausible, and the probable.

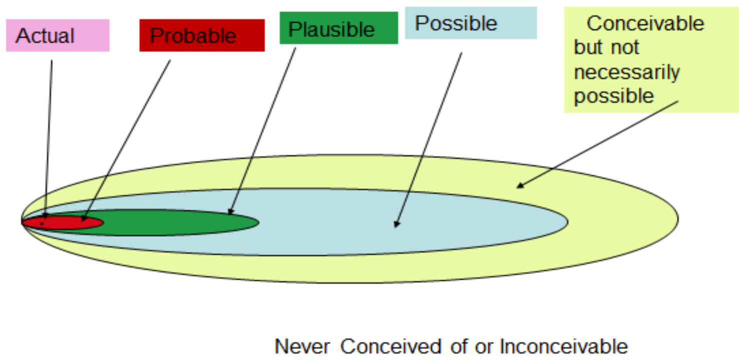


Figure 1. Categories of worlds. The dot indicates the actual future, with all possible outcomes depicted.

The diagram merits some consideration. It depicts all possible outcomes as a subset of all those that are conceivable; all plausible outcomes as a subset of those that are possible; all probable (or not improbable) outcomes as a subset of those that are plausible; and the actual outcome as located within the realm of the probable. Note that except for the dot representing the actual, all other descriptions of the future world in this diagram, be they probable, plausible, possible, conceivable, or never conceived of, can be classified as "counterfactuals"—accounts contrary, or counter, to what the world actually was, or what it became.

It is important to note that although people might like to imagine that the landscape of the future is as orderly as this depiction suggests, that landscape is in fact likely to be considerably messier and more complex. For example, the ratio of the possible to the conceivable may be substantially greater than we think. Some of the outcomes we might consider probable may in fact be not only implausible, but downright impossible. The "actual" world that emerges may be one of the variants not considered "probable," but only "plausible." Even some of those possibilities we consider relatively probable may be merely possible, or actually impossible. For illustrative purposes, Figure 2 incorporates these potential misconceptions.

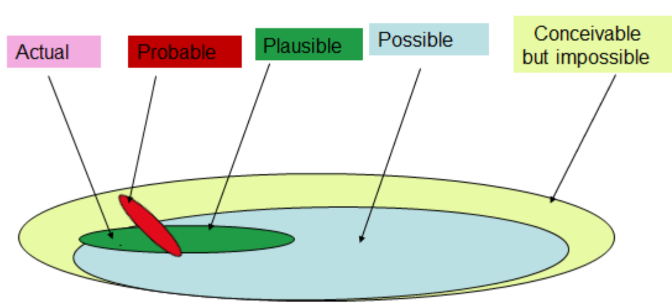


Figure 2. Categories of worlds if imagined incorrectly. The dot indicates the actual future, with possible outcomes depicted with real-world messiness.

Despite the difficulty of producing a reasonably accurate surrogate for the contours of what should be considered “possible,” precisely that surrogate is required for any forecasting tool to be consistent with the idea of “social radar.” Whatever technique modelers use to accomplish this task with respect to the future of a complex society, it must be governed by principles or be based on assumptions that enable what is produced to be treated as not only logically but also empirically possible. The technique must also be capable, at very low marginal cost, of generating large numbers of empirically realizable multidimensional trajectories or chronologies.

4. Results

The balance of this paper uses the Virtual Strategic and Forecasting Tool (V-SAFT) as an example to explain how a “social radar” model could satisfy these requirements.[3] The discussion then employs the state space of the future produced by V-SAFT as a target for queries designed to distinguish plausible and probable futures from those that are merely possible. It also covers how the tool can monitor change across regularly updated versions of that state space in order to generate indications and warnings, and can offer opportunities for what-if experiments to help adjudicate disputes over the implications of different assessments of key variables in the real world or to conduct what-if experiments.

4.1. V-SAFT Architecture and Processes

As displayed in Figure 3, V-SAFT incorporates model-building, experimentation, and analysis. Most processes are automated or semi-automated. In the left-hand column, under model building, the tool transfers data on geographical and administrative districts in a country to a pixelated computer grid in a form that can be integrated within the frame of a PS-I model. PS-I is a multi-use, agent-based modeling platform developed by Lustick Consulting for building and employing complex virtualization models employed in forecasting and analysis based on cellular automata.

[3] V-SAFT technology, developed by Lustick Consulting, is a stand-alone offshoot of work done within the Worldwide Integrated Crisis Early Warning System (W-ICEWS) team at Lockheed Martin Advanced Technology Laboratories, a project funded by the Department of Defense’s Human Social Culture Behavior Modeling program.

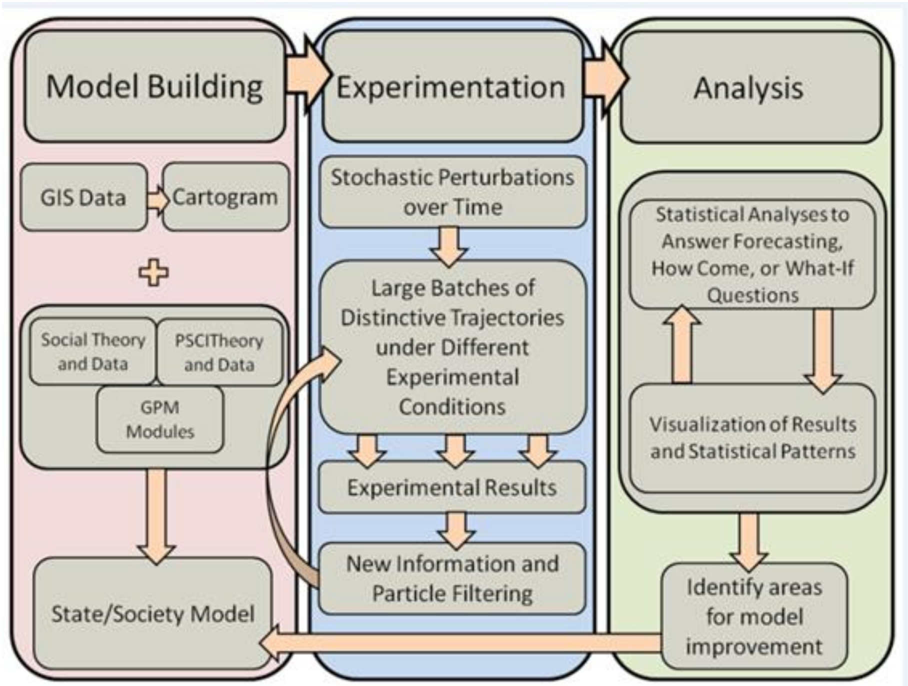


Figure 3. V-SAFT architecture and processes.

A typical country model can involve between 1,000 and 4,500 agents. As indicated at the top of the left-hand column in Figure 3, model building begins by mapping the target country (or sub-region) into PS-I. That landscape is then loaded into the Generic Political Model (GPM). The GPM condenses and federates a variety of political science theories about how states and societies operate and relate to one another. Although no social science theories have the certainty of some physical laws, all analysts naturally, but unselfconsciously, use theories they believe in to produce judgments about the future and conclusions about the likely effects of alternative assumptions or courses of action. The GPM and other modules encode relatively well-corroborated, even consensual theories developed by political scientists by translating them into micro rules for agent behavior, communication, and updating (Garces & Alcorn, 2012; Lustick, Alcorn, Garces, & Ruvinsky, 2012). The GPM then uses demographic, cultural, electoral, economic, and subject matter expert-derived data, including information on elite networks, to endow agents with attributes that render the model consistent with and tuned to realities in the target country at a specified time. Those attributes include a repertoire of currently available affiliations, or identities, with one among them activated, i.e., publicly on display, at any point in time.

A key module attached to the GPM is the Dynamic Political Hierarchy, which establishes the "dominant identity" or dominant "group" at each succeeding time step. By then determining patterns of overlap or isolation among various groups as reflected in the identity activation of agents and their identity complexions, the Dynamic Political Hierarchy sorts agents into key political categories: dominant, incumbent, regime, system, and non-system. When agents

dissatisfied or angered by their circumstances mobilize legally, semi-legally, or violently, they act. The type of action they take depends on their position within the overall constellation of power, affiliation, and commitment prevailing at that time within the model (Lustick et al., 2012).

In the middle column of Figure 3, "Experimentation," V-SAFT sends individual models forward in time. After a standardized "burn-in" period, each model time step represents approximately one week, with 60 time steps taken as a year. As a standard, V-SAFT generates 1,000 distinctive trajectories. Two stochastic elements ensure the distinctiveness of each trajectory: (1) a randomized distribution of agent attributes at t=0 that produces a unique version of the model consistent with our knowledge of district-level affiliations and sentiments and including the density and communication patterns of various influence networks, and (2) a unique, stochastically produced and recorded sequence of small perturbations in the bias assignments of affiliative identities that is associated with each model run. These perturbations act as a source of exogenous shocks that take place below the analytic horizon. V-SAFT sets the size and regularity of these shocks within a standardized range across all models, but can be adjusted for political environments judged as unusually calm or turbulent.

The developers ran elaborate sensitivity studies that involved measuring variance, means, and kurtosis across sample sizes up to 10,000. The findings strongly suggested that more than 1,000 runs per model condition would yield sharply diminishing returns in terms of producing interesting variations.

For each country model run with V-SAFT, we view the 1,000 trajectories as chronicles depicting the state space of the ways in which events could unfold during the coming year in the model's target country. In effect, then, we treat this set of trajectories as if it were the "possible" futures consistent with our best knowledge of the present, as condensed into the model. In precise terms, the trajectories represent the set of futures for which our model has provided "existence proofs"—proofs that the sequences of events tracked in these futures could be realized, assuming the correctness of the model and the reliability of the computer's implementation of the model's routines.

Every month we update each model with significant new sources of data (elections, censuses, subject matter expert reports, etc.) that become available. Models are also updated by an automated process that compares the first month of each new trajectory of a possible future to information about protests or violence that actually occurred in the country under study during the previous month to eliminate the subset of futures that can no longer be considered consistent with the country's "present." We run the model until we have collected a set of 1,000 trajectories, each consistent with the country's general condition at t=0.

Having thus produced the target for our "social radar" signals, we move to the third column in Figure 3: analysis. We address standardized queries about events, patterns, and outcomes of interest to the data base containing information about all 1,000 trajectories. Answers to these queries are equivalent to the bounce-back signal received by a radar installation that indicates the location, shape, direction of movement, and velocity of the target.

Displays of the data that emerge from these queries communicate a great deal about the contours of the state space of the future as suggested by the behavior of the model. V-SAFT then uses features of this state space to generate forecasts that distinguish among probable, plausible, or merely possible outcomes. The aim, again, is not to make "point predictions" of the "actual" future in any detail, but to give users systematic, quantifiable, and time-sensitive indications and warnings about EOIs. Since the data are recorded within specific trajectories, we can identify the conditions that tend to produce desirable or undesirable outcomes, whether relatively common or extremely rare, and use them to design specific and cost-effective mitigation strategies.

4.2. Queries

With respect to the "social radar" model of forecasting, we have noted that the "target" of the signals emitted by the radar instrument is the simulated state space of the possible for the country, region, or population under study. But what are the signals? "Social radar" must send standardized signals toward targets of interest to gain information from the distinctiveness of the patterned reflection of those signals. Radar operators identify different types of objects, birds, fighter aircraft, bombers, helicopters, etc., by their characteristic signatures. Similarly, V-SAFT operators use queries directed toward the data resulting from the production of 1,000 simulated futures. Responses to these queries reflect the contours of the state space of the country's possible futures. Visualizations of the answers to these queries are the equivalent of visual images on a radar scope and can be interpreted in standard ways to conduct analysis of the target and the direction and velocity of events.

4.3. Forecasts

Each month human analysts draft a summary forecast for each country model, based on a series of visualizations focused on a variety of dimensions. We use the summary forecast for Bangladesh for the year March 2013–February 2014 to illustrate the production of these forecasts from data displayed in these standardized visualizations. Unless otherwise noted, all visuals are available on the web for inspection and drill-down, as are operational definitions of terms.

Here is the forecast:

> V-SAFT's Bangladesh model forecasts a somewhat more than 75% probability of a sustained domestic political crisis between March 2013 through February 2014 and only a 10% probability of avoiding any sort of domestic political crisis during this period. Insurgent activity and incidents of ethno-religious conflict have a roughly 75% probability of appearing in this period, but the likelihood of these activities sustaining themselves for three months or more is very low (below 3%). These probabilities remain more or less the same across the entire forecast period. Nor do probabilities vary widely depending on the complexion of the governing coalition. Under a broad-based nationalist government, a business dominated coalition, or one based on Bengali appeals that is yet not dominated by the Awami League, Bangladesh has the best chance of enjoying a year relatively free from instability or severe instability. But the model shows a wide variety of different coalitions capable of emerging, most of which are associated with some significant instability or severe instability. Probabilities for at least one of these coalitions range from a low of 15% in governments

> dominated by non-partisan nationalists or business elites, to a high of nearly 65% under governments oriented toward narrow civic and technocratic appeals. Compared to last month's forecasts, a Muslim dominated government is no longer evaluated as plausible, while a business dominated government is to be considered plausible, and not merely possible. V-SAFT's overall assessment for the coming year is that governing elites in Bangladesh will likely face higher than average amounts of illegal and violent political mobilization over the coming year. This represents a substantial trend across the last five months of V-SAFT forecasts for Bangladesh. Keeping in mind what is normal for Bangladesh, this month's forecast registers not just an increasing probability of instability, but an increasing probability of severe instability. (Lustick Consulting, 2013)

The summary forecast begins with probabilities for key EOIs of historical importance for U.S. civilian and military planners concerned with Bangladesh. The "somewhat more than 75%" likelihood of a sustained domestic political crisis (DPC) over the forecast year and the unlikelihood of Bangladesh avoiding any period of domestic political crisis during that time frame are read off the "High Impact Possibilities" chart (Figure 4).

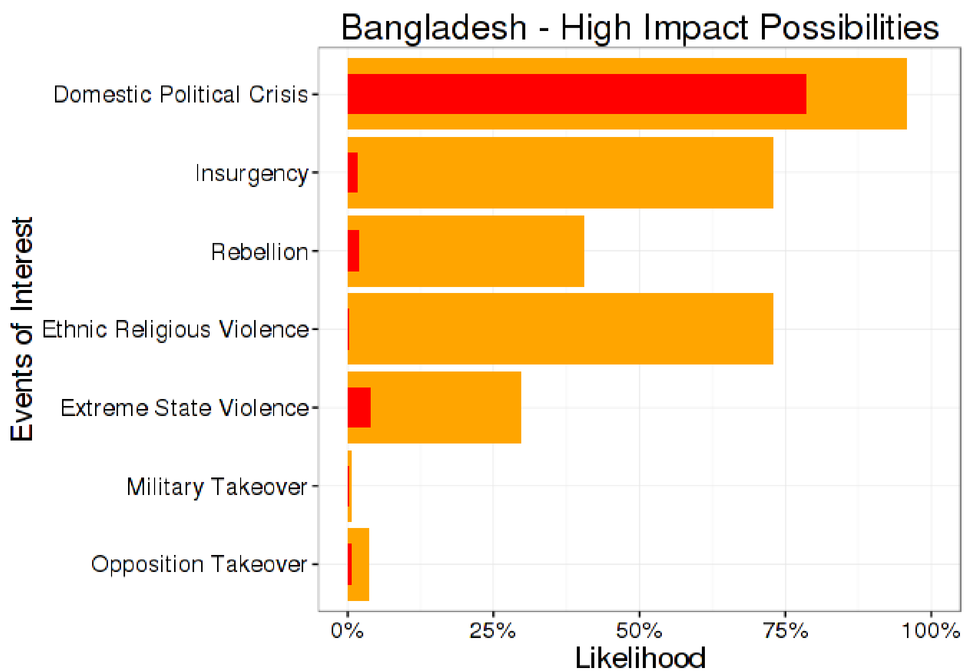


Figure 4. Probabilities for key EOIs of historical importance in Bangladesh such as the 75% chance of a domestic political crisis.

The extended "occurs" bar for "Domestic Political Crisis" shows that 90% of the weeks comprising all 1,000 simulated years of possible Bangladesh futures in the model contain behavior coded as corresponding to the definition of a DPC: organized, mostly nonviolent opposition to the government that is significant enough to threaten the integrity of the ruling coalition. In practice this definition must render a description of what agents in the Bangladesh model are doing in a language the computer can understand. For illustrative purposes, the operational definition of DPC is: "DPC exists in a timestep when the aggregate influence of protesting agents (protest) multiplied by the protest_threshold (6) is greater than the aggregate influence of the dominant identity (data$dominant_activation)." The routine that implements this category as a rule for data collection is: dpc_exists = (protest*protest_threshold>data$dominant_activation). The bar at roughly 55% likelihood indicates the "slightly more than 75%" probability of a sustained DPC, showing how large a subset of those weeks were occupied by a DPC that lasted at least three consecutive months.

The summary forecast also draws attention to the likelihood of at least some insurgent activity or ethnic-religious violence. However, in view of the very small size of the red bars in those categories, the forecast notes that sustained insurgencies or periods of ethnic-religious violence occurred so rarely in this set of trajectories that they should be considered implausible—in other words, possible, but extremely unlikely.

How are these probabilities for specific EOIs distributed over the forecast year? Figure 5 shows the months of the coming year on the x-axis and proportions of futures in the state space registering EOI activity on the y-axis. Thus, as noted in the summary forecast, we see that "[T]hese probabilities remain more or less the same across the entire forecast period, with a slight trend toward increasing risk after April 2013."

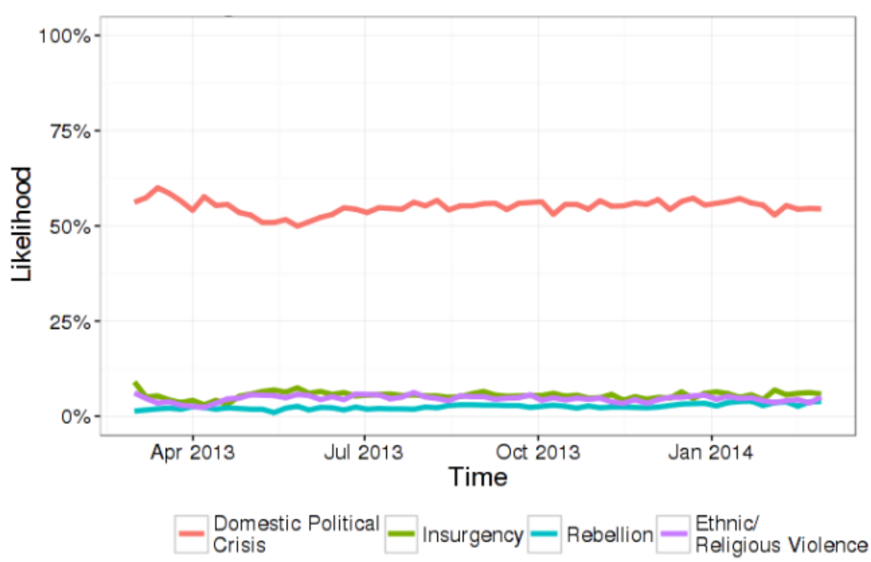


Figure 5. Probabilities for key "events of interest" in Bangladesh over the forecast year, with DPC relatively stable at 50%.

The summary forecast indicates that instability, including severe instability, is associated with many different constellations of political power anticipated as plausible within the forecast year. In Figure 6 different groups or political appeals that the model identifies as plausibly able to play a dominant and organizing role in Bangladesh governing coalitions over this time period are arrayed on the x-axis. The width of the bar associated with individual dominant groups or identities signifies the proportion of weeks within all 1,000 trajectories during which they are dominant. The width of the vertical segments in each column indicates how that amount of the state space is divided into periods of “calm” (green), “intense politics” (blue), “instability” (yellow), and “severe instability” (red).

Going somewhat beyond the explicit statements in the summary forecast, we can observe that while the most likely coalitions—those dominated by nationalist, Bengali, or Awami League ideas and elites—hold out a nearly 80% chance of avoiding instability or severe instability, no government that the model deems plausible has more than a 15% likelihood of enjoying calm throughout the year. A government based on alliances led by bureaucratic state elites faces the greatest likelihood of both instability and severe instability.

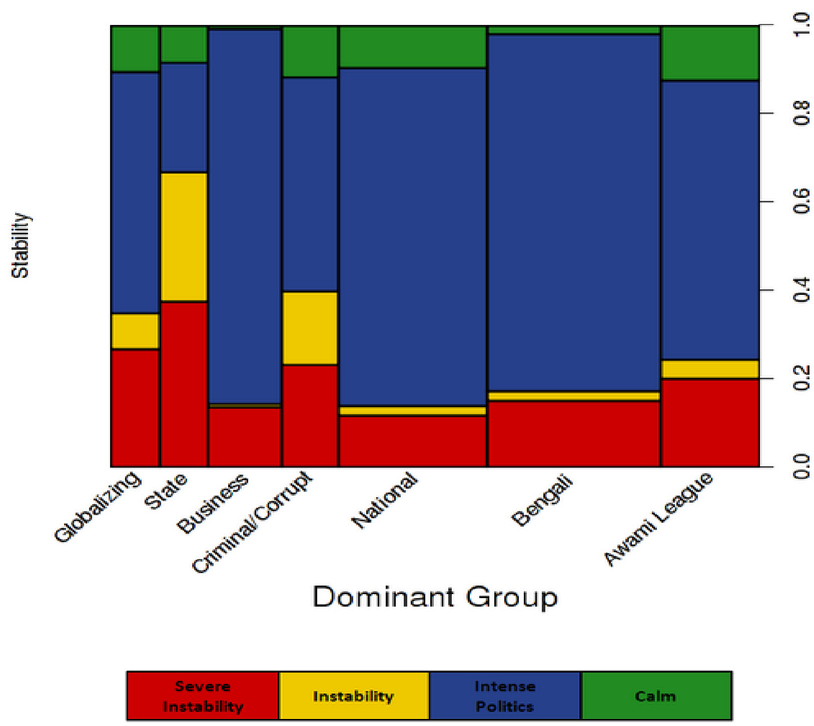


Figure 6. Dominant groups and levels of instability in Bangladesh. Along the x-axis are different groups identified by the model as plausible anchors of ruling coalitions in Bangladesh in this time period. The width of the columns associated with political dominance by different groups signifies the proportion of weeks when they are dominant, the width of the bars within each column indicates how that amount of the state space is divided into periods of “calm”, “intense politics”, “instability”, and “severe instability”.

By probing more deeply, we can see which groups are allies, opponents, or radical opponents of the government when bureaucratic state elites dominate the coalition (Figure 7) or when "globalizing, Western-oriented" elites dominate (Figure 8). We see that these types of governments, when they have significant allies at all, tend to rely on corrupt and criminal elements and on the (highly corrupt) business community. In Figures 7–9 and Figure 11 groups and identities listed along the x-axis are arrayed from left to right in order of decreasing "aggregate influence" during the periods of dominance by the group named under the column on the extreme left. V-SAFT computes aggregate influence for each group for any time step by summing the individual influence of agents activated on that identity.

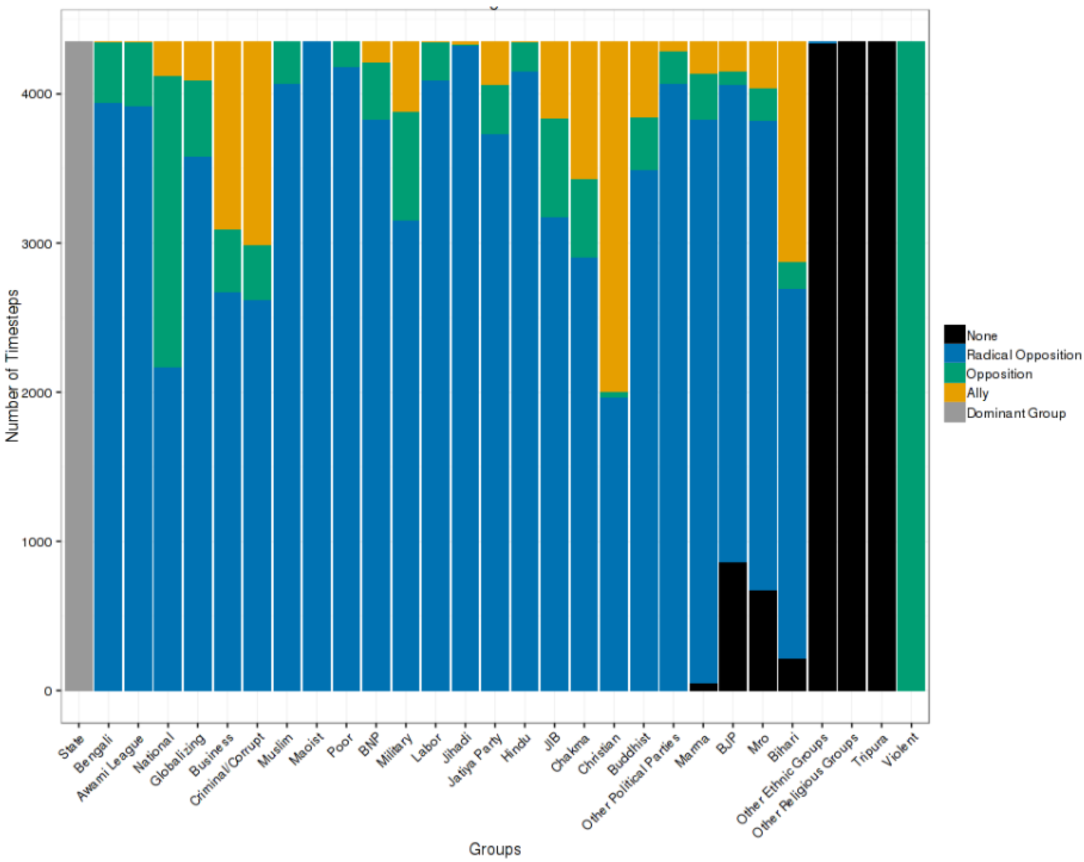


Figure 7. Domestic political hierarchy levels during State dominance. Groups are shown along the x-axis. The y-axis is the number of model time steps within the total number that featured the State identity group as dominant. The colored bars comprising the columns report the proportion of State-dominant model time during which each group was categorized within the DPH as either ally, opponent, or radical opponent.

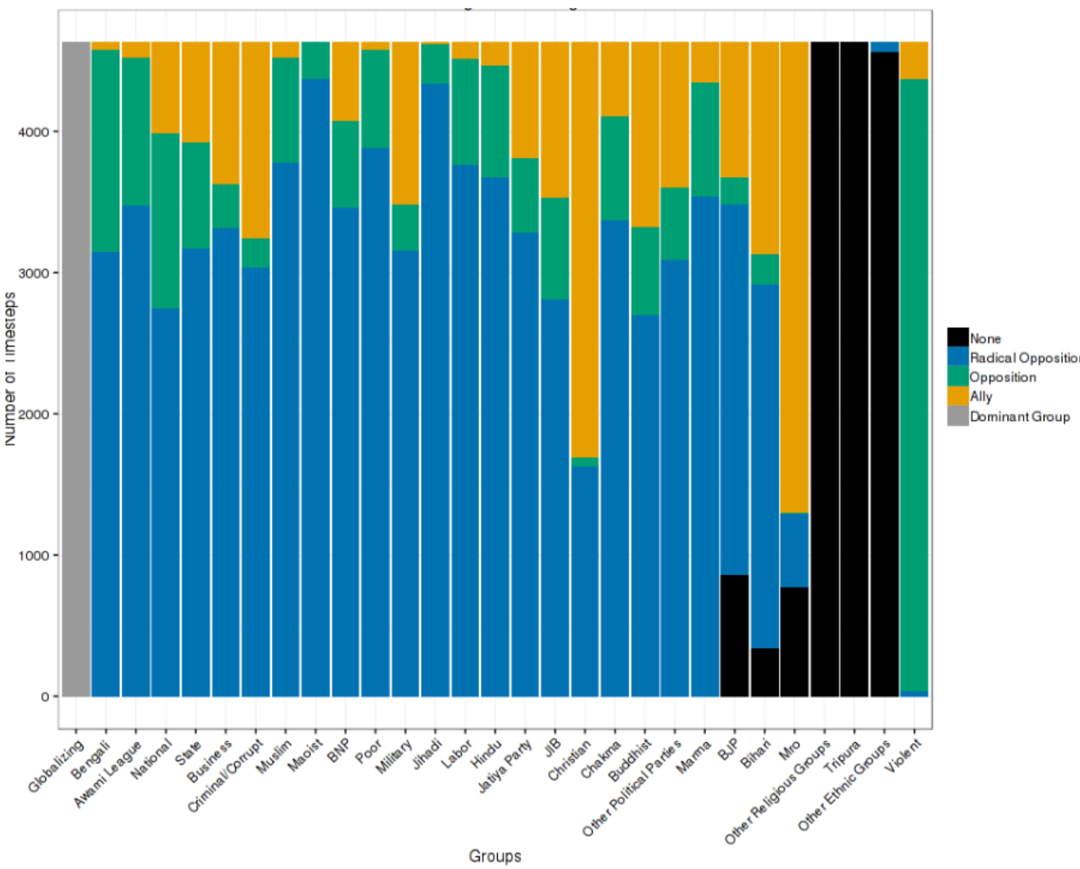


Figure 8. Domestic political hierarchy levels during Globalizing dominance. The groups are shown along the x-axis. The y-axis is the number of model time steps within the total number that featured the "Globalizing" (Western-oriented) identity group as dominant. The colored bars comprising the columns report the proportion of Globalizing-dominant model time during which each group was categorized within the DPH as either ally, opponent, or radical opponent.

As noted in the summary forecast, in the relatively unlikely, but still plausible, circumstance that business itself organizes a governing coalition—relying again on state bureaucrats, globalizers, and criminal-corrupt networks—prospects for intense politics, if not calm, appear to improve considerably. We can see why this occurs by considering the display in Figure 9, which shows that when business dominates, the largest groups in Bangladesh are much less likely to adopt a radical oppositionist posture (the blue portion of columns on the left of the display) toward the government than when state bureaucrats, globalizers, or criminal-corrupt networks (not shown) dominate.

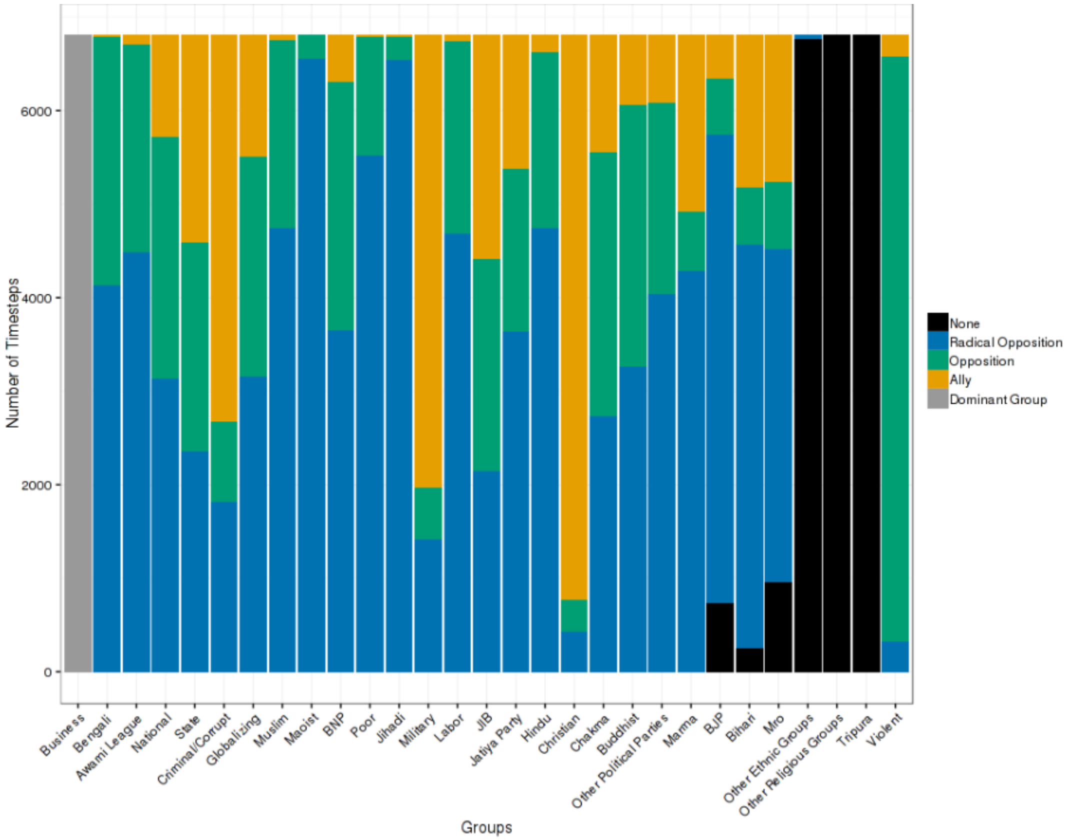


Figure 9. Domestic political hierarchy levels during Business dominance. The groups are shown along the x-axis. The y-axis is the number of model time steps within the total number that featured the Business identity group as dominant. The colored bars comprising the columns report the proportion of Business-dominant model time during which each group was categorized within the DPH as either ally, opponent, or radical opponent.

Comparing the state space mapped by running V-SAFT's Bangladesh model for the year beginning March 2013 to mappings produced in earlier months can help identify general trends. For example, in Bangladesh, Islamist-dominated governments appeared prominently enough in the state space to justify treating that outcome as plausible in each of the six previous months' forecasts (meaning that it appears in at least 3% of the space of the future). For the year beginning in March 2013, however, the likelihood of Islamist governments dropped below the 3% threshold. Accordingly, although such regimes appear in the display of plausible governments for the year beginning February 2013 (on the left in Figure 10), they do not appear in the display on the right—for the year beginning March 2013.

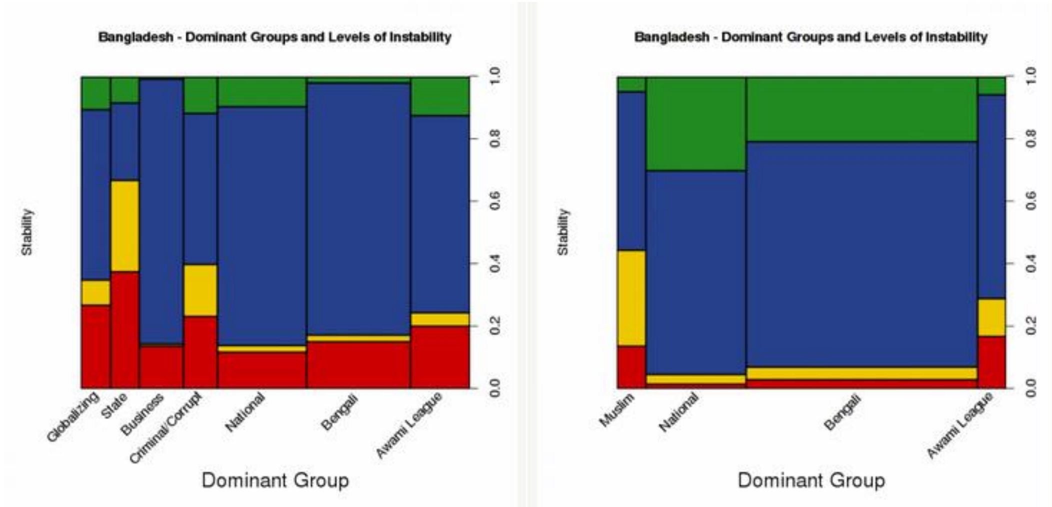


Figure 10. Dominant groups in Bangladesh. The x-axis are the dominant groups, the first y-axis is stability, and the second y-axis is the percentage of the space in which the forecast holds. For February 2013 (left) x group appears at 3% and in March 2013 (right) it drops below that.

On the other hand, by noting the thin gray line at the bottom of the column marked “Muslim” in the “Political Status by Group” display in Figure 11, we can see that V-SAFT still charted a Muslim-dominated government as possible, but just not “plausible” by the 3% rule.

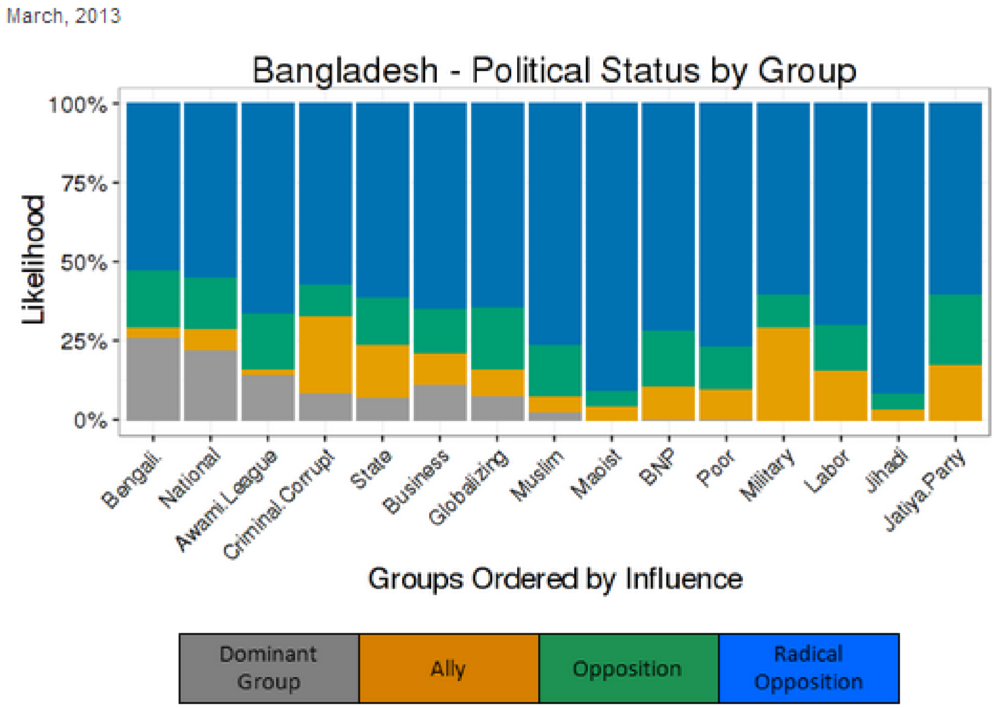
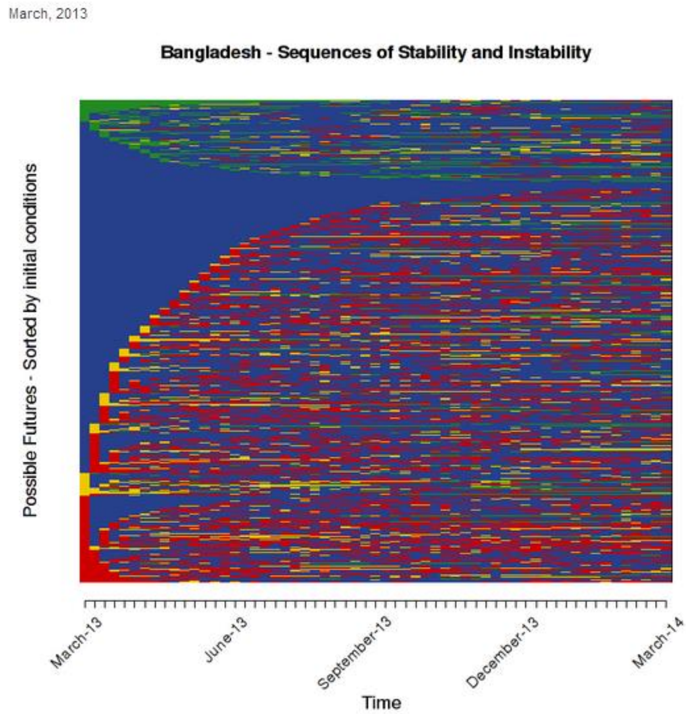


Figure 11. Political status by group in Bangladesh. This graph shows the likelihood of the dominant part of government coming from each group (x-axis).

The final portion of the summary forecast focuses on the trend toward an increasing likelihood of instability, and in particular of severe instability. This trend is most easily discerned by considering the group of six "sequence plots" displayed in Figure 12a – 12f, beginning with the forecasts made for the October 2012–September 2013 year and ending with forecasts made for the March 2012–February 2014 year.



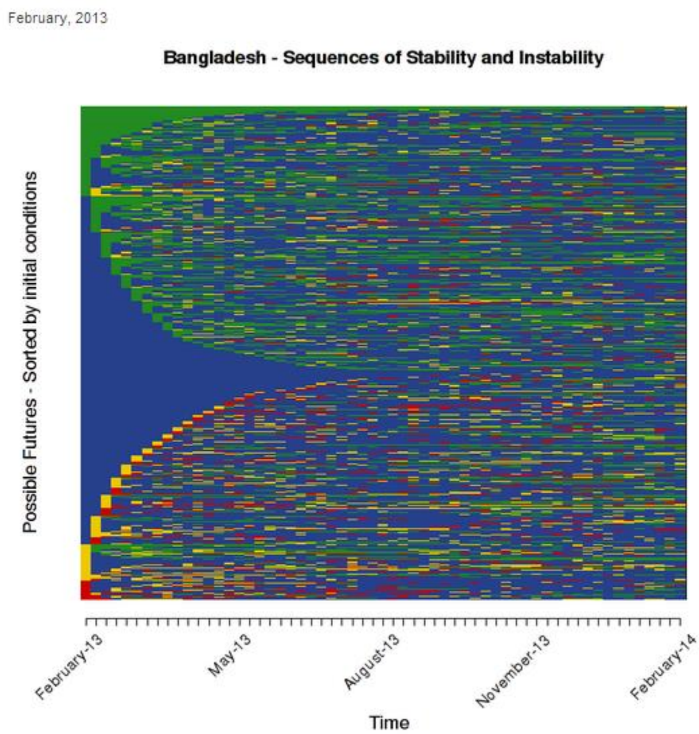
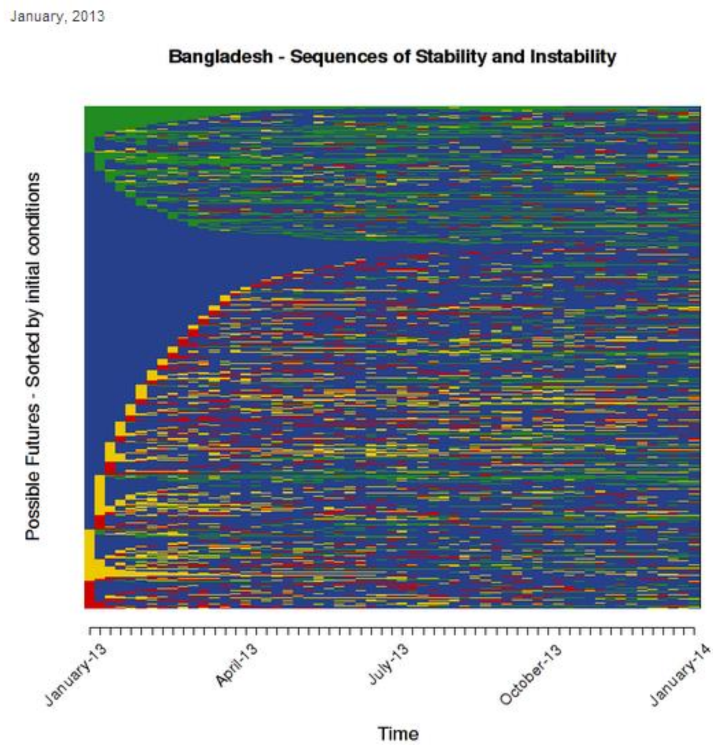


Figure 12a & 12 b. Six "sequence plots"—beginning with the forecasts for October 2012 until February 2014. Each trajectory (1,000) is traced horizontally by a single line to represent either calm (green), intense politics (blue), instability (yellow), or severe instability (red).



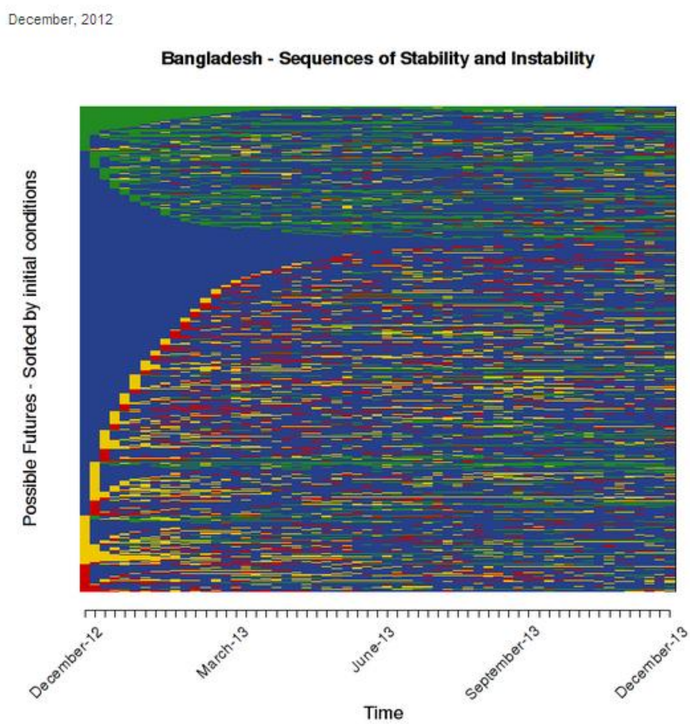


Figure 12c & 12d. Six "sequence plots"—beginning with the forecasts for October 2012 until February 2014. Each trajectory (1,000) is traced horizontally by a single line to represent either calm (green), intense politics (blue), instability (yellow), or severe instability (red).

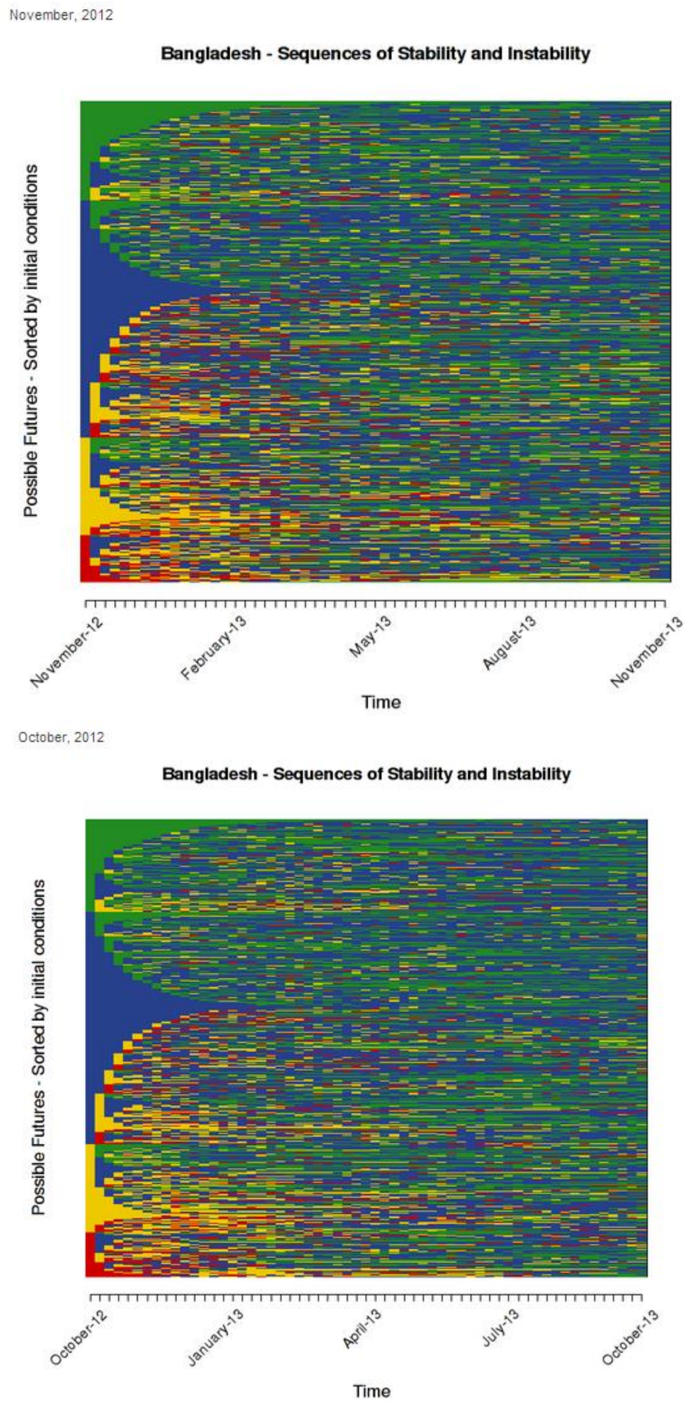


Figure 12e- & 12f. Six "sequence plots"—beginning with the forecasts for October 2012 until February 2014. Each trajectory (1,000) is traced horizontally by a single line to represent either calm (green), intense politics (blue), instability (yellow), or severe instability (red).

V-SAFT produces sequence plots such as those in Figure 12a-12f by stacking all 1,000 trajectories. Each week in each trajectory, traced horizontally by a single line, is colored to represent either calm (green), intense politics (blue), instability (yellow), or severe instability (red). The condition present at the beginning of the run and, within that group, by the length of time before that condition changes, determines the order of the stacking. Different horizontal patterns register different sequences of stabilization or destabilization. By noting the changing prominence of colors horizontally, we can gain a quick sense of time trends toward stabilization (becoming more green or blue) or toward destabilization (becoming more yellow or red). By noting the changing prominence of colors vertically, we can gain a sense of how much of the state space of the future—taking into account all 1,000 trajectories—is relatively stable or unstable across the entire square.

By comparing the balance of coloration across a series of sequence plots for the same country we gain a sense of trends in V-SAFT forecasts for that particular country. These can include increasing tendencies toward, for example, convergence on one color or bifurcation—relative disappearance of yellow or blue in favor of either calm (green) or severe instability (red). In the case of Bangladesh forecasts for the year beginning with October 2012 through the year starting in March 2013, we see a trend toward a pronounced shrinkage in the areas of green and yellow and expansion in the areas of blue and especially red, suggesting not just a decreasing probability of calm but an increasing probability of either intense political competition or severe instability.

5. Conclusion

Klein, Moon, & Hoffman (2006) characterize “sensemaking” as an “umbrella term for efforts at building intelligent systems” (p. 70). They imagined that such systems would display their intelligence by assembling and presenting data in ways that evoke understanding of the data as meaningful: that is to say enlightening or satisfying with respect to the ambitions, questions, or interests of users. They proceed to list common expectations for such systems—expectations that they suggest are important, but difficult to fulfill. Among those expectations are that the system will automatically fuse massive data into succinct meanings, process meaning in contextually relative ways, enable humans to achieve insights, automatically infer the hypotheses that the human is considering, enable people to access others’ intuitions, and present information in relevant ways. This chapter has sought to offer some encouragement with respect to forecasting, analysis, and visualization using the “social radar” metaphor and standard questions of interest to analysts of complex societies. Modeling has made significant progress toward satisfying these expectations in the eight years since these ambitions were listed, although much work remains to be done.

Only the accumulation of a large data set of forecasts can permit the kind of validation tests that alone would justify commitment of resources based on the automatic and semi-automatic production of forecasts, analyses, and visualizations of the sort now available with V-SAFT. The summary forecasts, which use narrative techniques to weave mnemonic meaning from standardized but still dauntingly complex data visualizations, can be produced automatically. But this will require considerable work based on studies of inter-coder reliability, dictionaries of possible combinations of reports from available displays, and algorithms to produce useful and

sensible prose depictions based on hierarchies of concern, trends along key dimensions, and significant anomalies. It is difficult to imagine that this distillation process could be completely automated, since one key aspect of forecasting is watching for events that could happen that have never happened before. Still, given the progress so far, one could quite reasonably expect that the kind of "intelligent machine" represented by V-SAFT could work well to focus the attention of human analysts on the kinds of problems for which they have, and will always have, a comparative advantage.

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12 Training for sociocultural forecasting: Current status and science and technology gaps[1]

Winston R. Sieck, Global Cognition

1. Introduction

Scientific disciplines across the board have struggled with the challenge of anticipating the future. From early predictions of the positions of planets to modern meteorological forecasting systems, humans have witnessed ongoing improvements in the ability to foresee events. Forecasting within the sociocultural sphere is no exception. Although many scientists are highly skeptical about the ultimate prospects of forecasting phenomena in the area of human social cultural behavior with any quantification or precision, others continue to plod along, making small gains along the way. Research programs that make any attempt to improve forecasting are highly susceptible to being labeled as failures, at least in part because they are plagued from the outset by unrealistic expectations of what they can accomplish in the short term. There is, however, a large difference between only being able to make a measured amount of real progress in the short term, and being unable to achieve anything at all. This chapter describes the current state of the science and technology related to training in sociocultural forecasting, and identifies gaps that research should address to develop capabilities for application in operational settings.

The following incident illustrates the intuitive use of native-level cultural knowledge to anticipate a political leader's actions. It provides several interesting points for discussion, not the least of which concerns how training in sociocultural forecasting techniques could lead to the development of a similar depth of understanding among non-native analysts and operators, at least about relatively narrow forecasting problems like this one (Sieck, McHugh, Klein, Wei, & Klinger, 2004, p. 19):

> The order came down to the head of the Bosnian analysis team on Sunday morning. The General needed the team to identify the propaganda themes that the Croats, Bosniacs, and Serbs would use by Monday. The team came in on a Sunday to put together a briefing.
>
> The team was multinational, with an American, a Dutch, a Turk, a Greek, and a German officer all working together. The American was the team leader. They had been studying the issue and background data for about nine weeks. The team had two separate interpretations and analyses of what was happening and what was driving events. The critical difference had to do with the Serbs, and the possibility that Milosevich would switch from Stalinist communism to pursue a religious angle in the upcoming months.

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> Most of the team members looked at the situation as purely a political process, Milosevich was promising the people who were his natural constituency a better day. They predicted that he would continue to promise a greater Serbia, with the Serbs dominating the political processes and the economic base of whatever was left of Yugoslavia. At dinner, the Greek and the Turkish officers got frustrated with the conversations of the others and finally said, “you don’t understand.” And the Turkish officer said, “look the problem is you’re thinking secular, and they’re not.” At this point, the reaction of the others was silence. It was one of those conversation killers. The Greek and Turk argued that the political message was no longer powerful enough to rally the Serbs, because there was no passion in it. They said that the only thing passionate in this was the religious separation. The Dutchman said that it might work, though he didn’t believe it. He just didn’t believe that a Marxist could get away with taking that line, or that he would have any credibility if he tried.
>
> After dinner the leader was approached by the Greek and Turk again. The team leader listened to them because it struck him as very unusual that people from traditional enemy countries came to the same conclusion and worked together to get the word to him. Also, he recognized that they had a very good feel for the culture, much better than the rest of the team. The rest had the distant political-analytical perspective, but they had a much closer, more personal, visceral perspective. The leader included the religious angle for the Serbs. In the end, Milosevich did take the religious angle. He made his first connection to religion in this conflict in May of 1992, several weeks after their prediction.

This case of sociocultural forecasting by a multinational intelligence team illustrates several aspects relevant to sociocultural forecasting:

- Like most forecast problems, it involves the prediction of some change from the status quo.
- The prediction made is categorical rather than probabilistic; the possibility of a religious theme would either be included or not, with no probability attached.
- Several team members seem extremely confident in their predictions, perhaps even overconfident.
- The Greek, Turkish, and Dutch members of the team all had substantial sociocultural knowledge, but that knowledge was of different kinds. The Greek and Turkish members were apparently better able to adopt the “native perspective” on the situation, appreciating what the Serbian population would and would not support.

This last point—about the potential value of understanding how people from a culture of interest think and make decisions before attempting to forecast their future behavior—raises especially interesting questions. This chapter addresses how sociocultural forecasters could be trained to make accurate predictions of culturally different others without the “visceral” understanding of the culture that only natives, and perhaps a few long-term expatriates, would share. It describes selected current science and technology in this area, as well as recommended future efforts to address this question.

The next section provides an overview of literature on probabilistic forecasting, with an emphasis on training analysts how to perform probabilistic forecasting. It then outlines special problems associated with forecasting in the sociocultural domain, along with their training implications. These include the nature and range of problems being forecast, from short-term political actions and events to long-term changes in population cultural values, beliefs, and behaviors. This section also discusses difficulties in representing emergent processes for forecasting, such as those that underlie sociocultural systems, and describes cultural resilience to aid in explaining why cultural change frequently does not happen or often has only temporary effects.

The third section presents an overview of literature and capabilities that support sociocultural forecasting and training. This includes work on concepts for training in cultural sensemaking and their relation to sociocultural forecasting, as well as training in the use of cognitive-cultural models for forecasting sociocultural behavior. In addition, it covers training implications of the Defense Advanced Research Projects Agency (DARPA) and HSCB-funded Worldwide Integrated Crisis Early Warning System (W-ICEWS) program, as well as forecasting training efforts within the Intelligence Advanced Research Projects Activity's (IARPA) Aggregative Contingent Estimation (ACE) program.

The fourth section summarizes science and technology gaps in this area that research has yet to address. The chapter concludes with a description of recommended next steps to move training capabilities toward operational usage.

2. Training Probabilistic Forecasting

Several research efforts have attempted to determine how best to train people to make better probabilistic forecasts. In general, they seek to train analysts in the process by which people generate forecasts, and to determine whether specific types of feedback lead to improved probabilistic forecasts. Such procedures could then be incorporated into forecasting tools and implemented within formalized training and education programs for specialists.

Probabilistic forecasting has the advantage of enabling forecasters to express uncertainty in their opinions using precise language that permits application of various quantitative metrics to assess the accuracy of sets of forecasts (Lehner, Michelson, & Adelman, 2010; Tetlock, 2005). These accuracy measures allow formal evaluation of forecasting systems, and also constitute a primary basis for generating different kinds of feedback to use in training forecasters.

Perhaps the most common measure of the accuracy of probabilistic forecasts is the mean probability score or "Brier score" (Brier, 1950; Yates, 1994). To obtain the Brier score over a set of forecasts, the probability score for each forecast is first calculated as $(f–d)^2$, where f is the reported likelihood that the target event will occur (e.g., the forecaster's stated probability that Iran and the United States will commence official nuclear program talks before 1 October 2013), and d is the actual outcome (coded as 0 if the target event does not occur and 1 if the target event does occur). Probability scores are calculated for each of many forecasts, and these are averaged to obtain the Brier score. As the equation shows, the Brier score is a measure of error in probability forecasts, so the lower the Brier score, the better the forecasts. Researchers have identified various means for

decomposing the Brier score into more fine-grained components that offer greater potential for detecting certain kinds of biases, and for formulating training applications based on feedback from accuracy measures (e.g., Yates, 1982).

The two most commonly discussed subcomponents of probability forecast accuracy are calibration and discrimination (see Figure 1). Calibration measures the extent to which a forecaster states probabilities that match various base rates, or the percentages of times that the target event actually occurs. Often, percentages of event occurrence are plotted for each probability judgment to produce a calibration curve (Lehner, Michelson, & Adelman, 2010). A forecaster might exhibit poor calibration in several ways, primarily over-prediction and overconfidence. Over-prediction means that the average of the forecaster's reported probabilities exceeds the actual proportion of times that the target events occurred. For example, suppose an analyst reports probability forecasts for 50 events such as the U.S.-Iran event given above. If the average of the analyst's probabilities is 70%, and yet only 25% of the events actually occur, then the analysts' forecasts are exhibiting over-prediction. Overconfidence typically refers to situations in which the analysts' forecasts are too extreme. To illustrate overconfidence, imagine a two-step procedure in which an analyst first states a categorical prediction as to whether or not each event will occur. The analyst then reports the probability that his or her categorical prediction is correct. If, over a set of 50 problems, the forecaster is correct in 58% of his or her categorical predictions, yet reports an average probability correct of 90%, then extreme overconfidence is evident. The two-step procedure aids in illustrating overconfidence, although the measure and the elicitation method are independent. Overconfidence can be computed regardless of how the probability forecasts are reported.

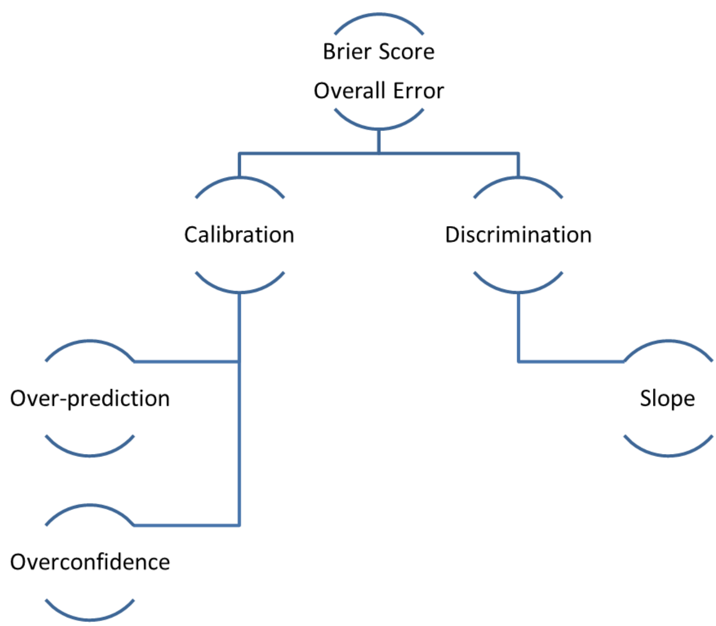

Figure 1. Subcomponents of probability accuracy.

The second general subcomponent of accuracy, discrimination, refers to a forecaster's ability to distinguish between situations when the target event will occur and when it will not occur. A simple measure of discrimination is the "slope" statistic proposed by Yates (1982). Slope is the mean of the probability forecasts for which the events occurred, minus the average of probability forecasts for which the events did not occur. The higher the slope, the better a person's forecasts distinguish between events that occur from those that do not.

It is important to recognize that a forecaster could do well on one of these aspects of probability accuracy but poorly on the other. That is, calibration and discrimination are distinct components of overall forecast accuracy. This has led researchers to examine whether the calibration and discrimination aspects of forecasting accuracy require related or distinct cognitive skills, for example, by attempting to determine whether training procedures that affect one of the measures also produce effects on the second measure (Stone & Opel, 2000).

3. Training to Improve Calibration and Discrimination

Most training in probability forecasting has emphasized improving calibration, presumably because it is generally viewed as simpler to achieve. Perhaps the most intensive training intervention for probability judgment using calibration feedback was conducted by Lichtenstein and Fischhoff (1980). In their study, trainees completed elevent training sessions involving 200 judgment problems. At the completion of each training session, the trainees received feedback on their probability accuracy that included graphs to show their calibration, as well as detailed performance statistics such as the Brier score and numerical measures of calibration. The researchers explained and discussed the feedback with the trainees for five to ten minutes. Following this rather intensive intervention, trainees showed a clear improvement in calibration.

Researchers have delineated several types of feedback potentially relevant to forecast training (Benson & Önkal, 1992). Giving trainees the results of their probability accuracy measures, as in the example above, represents just one kind of feedback, which is sometimes referred to as "performance feedback" (Benson & Önkal, 1992). Several researchers have suggested that performance feedback is a particularly effective method for improving calibration under suitable conditions (e.g., by reducing overconfidence). However, performance feedback has not proven particularly successful at increasing discrimination, since it contains no substantive information that would help trainees to determine whether or not a particular event will occur.

In order to disentangle the issues, researchers have also delineated another type of feedback potentially relevant to forecast training: environmental feedback (Benson & Önkal, 1992). Whereas performance feedback gives trainees information about the accuracy of their forecasts, including components such as measures of overconfidence, over-prediction, or discrimination, environmental feedback provides information about the event to be predicted. For our purposes, environmental feedback refers to any domain-specific information relevant to the forecasting task, such as associations between cues and outcomes. Various forms of cultural information relevant to a leader's decisions, for example, would be especially relevant to predictions in the sociocultural

realm. In contrast to performance feedback, environmental feedback appears to improve discrimination but not calibration.

In one study designed to test the relative benefits of distinct kinds of feedback, participants were asked to provide forecasts and given performance feedback. One group of participants received feedback on their calibration, while another group received feedback on their discrimination scores. These both reflect performance feedback, as they relay information as to how well the trainee forecast in the problem domain. As in earlier work, performance feedback regarding calibration improved participants' calibration scores but had no impact on discrimination (Benson & Önkal, 1992).

Subsequently, Stone and Opel (2000) explicitly contrasted the impact of environmental and performance feedback on the accuracy of probability judgments. They randomly assigned participants to performance feedback, environmental feedback, or no feedback (control) conditions. Their study procedure included three parts: pre-training probability judgments, training, and post-training probability judgments. The performance feedback group received individualized feedback regarding their calibration performance. The environmental feedback group received information in the form of a 30-minute lecture on a historical subject designed to increase their substantive knowledge about the topic of their predictions. All participants received a handout that described five to ten important characteristics relevant to the topic at hand. They then practiced using the new knowledge to re-analyze 20 of their probability judgment problems from the pre-training session. The control (no feedback) group completed an unrelated task during the training period.

Stone and Opel confirmed that performance feedback led to improvements in calibration, but not discrimination, and that environmental feedback led to improvements in discrimination, but not calibration. Importantly, the researchers also found that substantive training in the form of providing additional environmental cues and information can actually degrade calibration. In particular, after participants received environmental feedback, their overconfidence increased (Stone & Opel, 2000). The latter finding suggests that merely increasing people's knowledge about a particular area or domain, for instance by encouraging analysts to digest volumes of information about the culture of a region of interest, can lead to an increase in forecast confidence not matched by commensurate increases in accuracy.

Within the domain of sociocultural forecasting, this implies that knowledge of the culture or area is insufficient to accurately anticipate future events. Instead, training programs must also incorporate forecast performance feedback using measures of calibration. This represents an important issue from a practical standpoint, as it indicates that training methods that attempt to influence one component of accuracy (calibration or discrimination) may not have any impact on the other component. Table 1 summarizes these relationships.

Table 1. *Types of Probability Feedback and Their Effects on Performance*

Type of Feedback	Description	Effects on Accuracy
Performance	Information about components of forecast accuracy (calibration, discrimination)	• Improves calibration • No effect on discrimination
Environmental	Information about the event to be predicted, such as cultural information	• Can improve discrimination if information is diagnostic • Can harm calibration by increasing overconfidence

Stone and Opel concluded that calibration and discrimination reflect distinct cognitive skills, which they called calibration expertise and substantive expertise. Substantive expertise refers to domain-specific knowledge in a certain area, such as sociocultural expertise in a given region. Calibration expertise reflects the ability to render probability forecasts that exhibit neither over- or under-prediction nor under or overconfidence. Furthermore, distinct types of feedback and training are required to improve these different cognitive skills and thus promote overall expertise in probabilistic sociocultural forecasting.

4. Forecasting in the Sociocultural Domain

This section describes issues associated with forecasting in the sociocultural domain, as well as their training implications. For illustration, this section employs an example regarding crowd behavior in the Middle East and the Arab Spring.

One issue concerns the scope of problems being forecast, which can range from immediate reactions to medium-term political actions and events to long-term change in population cultural values, beliefs, and behaviors. First, analysts might use sociocultural knowledge and tools to predict local, immediate, transitory outcomes, such as newsworthy events of the day. For instance, Sieck, Simpkins, and Rasmussen (2013) investigated crowd member responses to security force actions in the Middle East. The cultural, behavioral, and situational factors they examined should aid in anticipating whether an Arab crowd would turn violent or remain peaceful in a time span of a few moments to a few hours. Training based on those models would enable U.S. personnel to make sense of, anticipate, and hence more effectively manage crowds in places such as Iraq (Sieck, Smith, Grome, & Rababy, 2010). Such training would also likely have aided an analyst to track events as they unfolded during the Arab Spring to forecast the likelihood of violent eruptions on the same time scale.

At a second level, sociocultural sensemaking might be used to predict outcomes in the middle term, such as changes in political leadership. An example at this level would be an analyst forecast of the likelihood that Hosni Mubarak would not remain as Egypt's leader as a result of the Arab Spring protests.

Finally, a third level concerns distant, long-term outcomes, such as changes in deep-rooted cultural values. A forecast problem at this level might address the likelihood that the Arab Spring and changes in political institutions within Egypt would reduce the cultural value of "power-distance" over the next decade. Power-distance measures the degree to which members of the culture accept and expect unequal distribution of power in the society (Hofstede, 2001). People in high power-distance cultures tend to be comfortable with the idea that their leaders (at the national, organizational, or family level) hold the lion's share of power. Middle Eastern countries tend to rank very high on Hofstede's power-distance index (Hofstede, 2001). For instance, if the cultural value placed on power-distance remains constant within Egypt, new governments and leadership would probably assume just as much control as their predecessors, since this is expected at a deep level by their constituents.

To date, most research and application of sociocultural forecasting has apparently focused primarily on the middle level. However, outcomes at this level may well not mean what we think they mean in terms of longer term, strategic-level implications. Sociocultural forecasting and persistent sensing of fundamental cultural values that represent long-term changes to societies constitute an important area for further applied research and development.

Consideration of long-term, fundamental cultural values leads naturally to a second issue in sociocultural forecasting: the need to understand why cultural change frequently does not happen or often has only temporary effects. An important factor associated with a culture's resistance to change is the looseness or tightness with which its members hold on to cultural norms: the standards by which members of the culture live. These norms represent the shared expectations and rules that guide the behavior of people within social groups, and as such are learned from and reinforced by parents, friends, teachers, and others as children grow up in a society.

Gelfand and a large international team investigated cross-cultural differences in the extent to which cultural norms matter to the members of the society (Gelfand et al., 2011). Some societies exhibit "cultural tightness," insisting on strong conformity to their cultural norms in all areas. Other, "culturally loose" societies tolerate far more deviance from the norms. Gelfand and colleagues theorized that tightness and looseness are reflected at different levels within a culture that mutually support one another. Specifically, Gelfand et al. (2011) described evidence related to four levels:

1. Ecological and Historical Threats. Hostile neighbors, disease, and dense populations increase the need for coordinated and disciplined action from the population. Factors such as these tighten cultural norms. As the threats diminish, adherence to norms becomes looser.

2. Sociopolitical Institutions. Culturally tight nations tend to have more autocratic governments, restricted media, stronger suppression of dissent, and more severe punishments for crime.
3. Everyday Social Situations. All kinds of interactions with fellow members of the culture are more formal in nations with tight cultural norms. These include situations at home, the workplace, school, places of worship, parks, and others. Loose cultures provide more room for individual discretion in such situations; a wider range of behavior qualifies as "appropriate."
4. Psychological Adaptations. People's minds become attuned to the different requirements of living in places with tight or loose cultural norms. Individual psychology then further supports the level of cultural tightness or looseness. People living in tight cultures become more focused on avoiding mistakes, are more cautious in their own behavior, and more closely monitor themselves and others for norm violations.

A sociocultural forecaster might take many cultural values and factors into account when generating a prediction. Cultural tightness or looseness of norms represents one of a small set of potential factors that specifically address tolerance for deviance and hence willingness to change at the cultural level. It is therefore a potentially useful factor to consider across many forecast problems. In addition, the Gelfand team's analysis of the issue in terms of the four mutually supporting levels provides an excellent illustration of the general factors involved in maintaining any cultural system in its current state.

5. Training in Sociocultural Forecasting

Several programs have addressed topics related to training in sociocultural sensemaking and forecasting, including the Office of the Secretary of Defense's Human Social Culture Behavior (HSCB) Modeling Program, IARPA's ACE program, and DARPA's W-ICEWS program. This section discusses selected research and development topics from each of these programs.

5.1. HSCB modeling program

Cognitive-Cultural Modeling

The HSCB program has sponsored the use of cognitive-cultural models that can aid in forecasting sociocultural behavior. Cognitive-cultural models are graphical representations of a culture's shared values, conceptions, and causal beliefs that influence decisions by members of interest in that culture (Sieck, 2010; Sieck, Rasmussen, & Smart, 2010). These models help cultural outsiders to assume the viewpoint of cultural insiders. Cognitive-cultural models also aid in identifying cultural elements that should receive high priority in training, and in anticipating the behavior of the members of the culture. In their most advanced form, cognitive-cultural models also represent quantitative information about the prevalence of the ideas included.

Researchers developed the models via Cognitive-Cultural Analysis (CCA). This process was originally termed "Cultural Network Analysis," but the name was changed to highlight the cognitive emphasis of the models, i.e., that the models seek to reveal how members of the culture think and make decisions. The CCA approach adopts the theory of "cultural epidemiology," which implies that ideas

can be studied using some of the same techniques that epidemiologists use to study diseases (Berger & Heath, 2005; Sperber, 1985).

CCA ensures that the cognitive aspects of a culture can be incorporated into practical use, such as forecasting and training applications, by identifying key decisions or judgments of interest as a first step. Once the key decisions have been determined, cultural analysts construct models which include the cultural ideas that directly influence those decisions.

CCA encompasses several techniques needed to build cognitive-cultural model diagrams. The primary representation format for CCA is the influence diagram, used very successfully for some time to map knowledge in decision analysis (Howard, 1989). Research has developed techniques to (a) elicit concepts, causal beliefs, and values from people in interviews or survey instruments, (b) extract the ideas from interview transcripts or other text material (e.g., text harvested from the World-Wide Web), (c) analyze the degree of commonality in ideas between cultural groups, (d) align and assemble consensus groups of ideas into maps, and (e) relate them to demographic variables. Although CCA seeks to represent the idea networks in a common, scientific format, it nonetheless maintains the content of cultural knowledge as expressed by members of the cultural group (Sieck, 2010). This is exactly the information that analysts need to acquire the visceral understanding described in the illustrative case at the beginning of this chapter.

The resulting cognitive-cultural models include estimates of the prevalence of such cultural ideas. Capturing the proportions of people who actually maintain the relevant beliefs provides a full description of the current cognitive state of a culture. With respect to prediction, prevalence information yields relevant status quo base-rates to which forecasters can anchor and then adjust to ensure forecast realism. In this way, cognitive-cultural models that include quantitative estimates of idea prevalence give forecasters environmental feedback in a form that has the potential to improve both aspects of probability accuracy: discrimination and calibration.

CCA is ideally suited to simulations using Bayesian modeling, although the application is somewhat different from Bayesian modeling applications that rely on expert inputs. In standard expert applications of Bayesian belief networks (BNs), researchers elicit structural and probability inputs from experts to determine the representation of a physical system, with the aim of accurately and quantitatively predicting key physical outcomes based on the experts' understanding of influences within the system. By contrast, in a cognitive-cultural modeling application the aim is to capture cultural knowledge in order to accurately anticipate the perceptions and decisions of members of cultural groups. The key principles governing application of BNs to cultural modeling are that BNs focus on the population, rather than on the individual psychological level of analysis; nodes represent concepts held in common by some percentage of the population; edges represent causal beliefs, also distributed across members of the population; and probabilities denote the prevalence of ideas in the population, not the strength of belief.

Projects sponsored by the HSCB Program have used CCA to develop several quantitative cognitive-cultural models of Afghan decision making based on interviews and a survey study of 400 Afghans from several different provinces (Sieck, Javidan, Osland, & Rasmussen, 2012). CCA and one of the

Afghan cognitive-cultural models were also used in the development of a prototype tool for simulating cultural behavior, known as the Cultural Belief Network Simulation Tool (CulBN) (Sieck, Simpkins, & Rasmussen, 2011). CulBN provides a user interface that enables the creation, visualization, and manipulation of input values in a cognitive-cultural model. The interface was combined with a standard BN simulation engine that could generate forecasts contingent on specific changes within the model (Sieck, Simpkins, & Rasmussen, 2011). The system allowed forecasters to interact with the model, for instance by entering hypothesized changes in certain elements and then visualizing the predicted consequences in terms of quantitative adjustments to cultural prevalence values. Some of the primary anticipated benefits of CulBN in supporting the training of forecasters include that it provides a coherent approach to constraining and making sense of a vast array of concepts, causal beliefs, and values, as they are relevant to particular decisions and behaviors of interest to the forecaster.

One of the challenges for novice sociocultural forecasters is managing the overload of information potentially relevant to a forecast. CulBN's structure may help reduce the amount and increase the relevance of information that analysts must take into consideration, which should support both forecast calibration and discrimination. In addition, experienced analysts can usefully share cognitive-cultural models to provide environmental feedback that can aid novice analysts in gaining expertise on specific topics relevant to their area of study. These possibilities should be tested in applied research settings.

Training in Cultural Sensemaking

Training in cultural sensemaking provides learners with cultural knowledge relevant to explaining culture-specific behavior, as well as metacognitive strategies for coping with unexpected behaviors and consequently acquiring new knowledge (Rasmussen & Sieck, 2012; Rasmussen, Sieck, & Osland, 2010). Such training may use cognitive-cultural models to provide direct and specific input to support novice thinking. Rasmussen et al. (2010) outlined a theoretical framework for cultural sensemaking that connects metacognitive skills to region-specific knowledge. They also described a novel approach to instructional analysis and design, specifically developed to identify learning objectives and content for training in cultural sensemaking. Demonstration of the method led to the development of a training booklet and materials that some military-cultural instructors have incorporated into their courses (Rasmussen & Sieck, 2010).

Within this theoretical framework, cultural sensemaking refers to the processes by which people make sense of and explain culturally different behaviors (Osland & Bird, 2000). In such cases, it is natural that peoples' initial perspectives are driven by expectations based on normal behavior learned within their own culture (Archer, 1986). An initial challenge within a cultural sensemaking situation or training simulation is recognizing when the models one would normally use no longer apply. Next, individuals seek the information they need in order to develop culture-appropriate understanding of the current situation. This provides a basis for projecting likely subsequent actions and, in the present context, for developing informed probabilistic forecasts.

An important metacognitive skill to support cultural sensemaking is the ability to build the knowledge required to explain and predict behavior. Further, this overall skill is embedded within a framework of related metacognitive skills that allow individuals to obtain, apply, test, and refine their cultural knowledge. These metacognitive skills are culture general in the sense they support attainment of culture-specific knowledge within any culture (Rasmussen & Sieck, 2012).

Instructional analysis for training in cultural sensemaking begins with Cognitive Task Analysis methods to identify culturally relevant situations for inclusion in a scenario-based training program (Chipman, Schraagen, & Shalin, 2000). The specific nature of the resulting scenarios would depend on the region of interest, as well as on the trainee's job (e.g., small unit leader vs. sociocultural analyst). Curriculum developers then use CCA to characterize both native decision making within these challenging situations and learner expectations regarding the native decisions. Specific knowledge-level learning objectives then result from comparing the learner models and native models to identify the gaps in learners' understanding and their misconceptions regarding how natives are likely to decide.

For example, in the application to Afghan decision making, the native cognitive-cultural model provided the target concepts for training U.S. Marines to understand Afghan behavior. New Marines with no prior deployments made open-ended assessments that were used to generate their expected models of the Afghan decisions and motivations. The program developers used a coding scheme to perform a quantitative assessment of the accuracy of these target learners' understanding of the cultural model and identify critical belief-value relationships that they either failed to perceive or had misunderstood. The knowledge-level (or cognitive-level) learning objectives for the training program focused on closing the gaps and remedying the misconceptions revealed through this assessment.

The cognitive learning objectives in the example above are culture- and job-specific, as is appropriate for trainees who must focus on a specific region for a year or more. Training in cultural sensemaking also includes culture-general learning or metacognitive strategies that build sensemaking competence. For example, in the Afghan-based demonstration project, developers identified learning objectives to improve information-seeking strategies by comparing the questions that the target learners asked to better understand the situation to the questions that expert cultural sensemakers tend to ask in order to create deep understanding (Sieck, Smith, & Rasmussen, 2008). Experts ask cultural sensemaking questions to obtain deeper insight into the belief-value relationships relevant to explaining and anticipating behavior. Generally, such questions take the form of why, why not, how, what if, etc. (Graesser, Baggett, & Williams, 1996).

The framework for training in cultural sensemaking describes a process through which culture-specific learning can contribute to culture-general competence. The underlying concept is to provide learners with baseline cognitive-level knowledge of the factors that influence the decision making of culturally different others in specific situations, along with the metacognitive strategies that enable the learners to progress further by building on that initial, informed understanding. This should enable trainees to learn more efficiently from the complex, real-life cultural situations they will encounter on the job, and further expand their storehouse of experiences. Applied

research has tested the principles of this training approach, but future work is needed to develop a full training system based on the approach and test its efficacy at supporting sociocultural forecasting.

5.2. DoD's W-ICEWS program

DoD's W-ICEWS program focused primarily on developing and testing computational models to anticipate and understand instability and violent political conflict (Kettler & Hoffman, 2012; O'Brien, 2010). The developers envisioned a system that could provide military commanders with predictions as to which countries would most likely experience domestic and international crises, with forecasts ranging from the short to the long term. Teams in the W-ICEWS program developed competing models to predict historical cases of instability using data from news and other country background information.

DARPA designed W-ICEWS to enable the comparison and evaluation of several different forecasting approaches. A team led by Lockheed Martin-Advanced Technology Laboratories (LM-ATL) developed the system that generated the most accurate forecasts, making correct predictions about 80 percent of the time in Phase 1, and improving to around 95 percent accuracy in Phases 2 and 3 (Kettler & Hoffman, 2012). LM-ATL used Bayesian methods to produce forecasts by integrating a few distinct kinds of modeling systems, such as agent-based models, logistic regression models, and geospatial network models. The models took a range of factors into account, including sociocultural information such as ethnic-political identities, social similarity profiles, authority structures, trade ties, flow of people, and geographic organization. Interestingly, researchers found that the system predicted few cases of civil war at probability levels above 50%, and some of the models apparently never generated probabilities greater than 30% (O'Brien, 2010).

To determine the possible training implications of this research and development effort, consider that models of this type would likely serve as inputs to an analyst or planner responsible for informing a command team about sociocultural events of interest. In such cases, the analyst should have a conceptual understanding of the models and the process by which they arrive at their predictions. Understanding the concepts underlying model aggregation, and especially the reasons why aggregated, hybrid models often outperform others would also be extremely useful. This level of understanding is essential to ensure that operators trust and incorporate the forecasting system predictions into their briefings and recommendations (cf. Wedgwood, Ruvinsky, & Siedlecki, 2012).

Beyond this, operators need to understand the range of predictions produced by the systems: specifically, how to interpret low probabilities and consider base-rate information (overall proportions of times that events occur). A sizeable body of research shows that superior forecast performance results from giving substantial weight to base-rates, and that computational models using formalized estimation make optimal use of the base-rate information. Models that produce only slight adjustments from base-rates do so because the specific factors they rely on are only weakly informative as to the events being predicted. This occurs because few organizations currently have access to sociocultural information that discriminates much beyond base-rate

predictions. Analysts and operators must learn to appreciate that the specific sociocultural information they have on hand is most likely not as discriminating as it intuitively appears.

5.3. IARPA's ACE Program

IARPA's ACE program on contingent forecasting of international actor reactions to possible U.S. and third-party actions has also undertaken efforts to support training in applied forecasting. According to IARPA (2013), the project uses crowdsourcing techniques to "dramatically enhance the accuracy, precision, and timeliness of forecasts for a broad range of event types, through the development of advanced techniques that elicit, weight, and combine the judgments of many intelligence analysts." An example forecast problem is: "Will Iran and the United States commence official nuclear program talks before 1 April 2013?" The resulting forecasts span a global domain, from the outcome of presidential elections in Taiwan to the potential of a downgrade of Greek sovereign debt, which presents interesting challenges in terms of bringing relevant regional and cultural knowledge to bear. IARPA evaluates ACE predictions using the widely accepted Brier score, or average sum of squared differences between probability forecasts and the actual outcomes, as described previously (Brier, 1950).

With respect to training, one project site employs a "Forecasting Ace University" that provides detailed information on specific aspects of forecasting, along with a set of forecast training modules (Warnaar et al., 2012). The training topics include the scoring rules used by the site, a description of high-stakes forecasting, calibration of forecasts, the use of base-rates to alleviate over-prediction, and ways of evaluating the credibility of information sources to promote better discrimination. The system delivers computer-based training (CBT) modules on several topics over the web (i.e., e-learning). Each module includes multimedia presentations and interactive exercises along with explanation feedback to aid concept acquisition and application. Site users also receive information and feedback relevant to specific forecasts, such as information about others' forecasts and rationales (environmental feedback), trends in crowd forecasts over time, and information about their own forecast accuracy (performance feedback).

Another team has also sought to determine how best to train and support forecasters, and has reported demonstrated gains due to training (Ungar, Mellers, Satopää, Tetlock, & Baron, 2012). This team initially expressed some skepticism about the possible benefits of allowing individual forecasters to share information (a form of environmental feedback) or to receive training in the use of probabilities, including performance types of feedback. For example, they noted that permitting experts to share information about their predictions and reasoning had the same potential of leading to "group-think" as of leading to better models of the phenomenon. On the probability training side, they noted that conceptual knowledge of probability and statistics does not disable forecasters' natural intuitions and use of flawed heuristics when making predictions. They also pointed out that systematic cognitive biases, such as overconfidence, might be more readily corrected using mathematical transformations during the aggregation of forecasts across members of the "crowd."

Despite their initial pessimism, the team experimentally tested the effects in a controlled fashion. Conditions within the experiment included probability training and no training, as well as

forecasters who worked independently and those who were assigned to teams of 15 to 20 members who consulted with one another over each forecast (the full design included several other conditions as well). Their primary findings included that the team condition, which enables environmental feedback in the form of sharing region-specific and other information related to each forecast, significantly outperformed the independent forecaster conditions. In addition, the researchers found probability training was beneficial, and indeed augmented the benefits of the team condition, such that the probability training proved most effective for people who made forecasts within team environments.

Another interesting aspect of W-ICEWS and ACE is that both directly embed training as a core component of the forecasting system. Researchers should explore additional development approaches along the lines of integrating forecast systems and forecast training systems.

6. Advancing Training in Sociocultural Forecasting

The efforts surveyed above reveal several science and technology gaps that researchers should address to move this capability area toward operational usage. This particular sub-area of sociocultural sensemaking is perhaps less developed than others, so the following discussion primarily addresses topics that applied research should resolve, such as potential skills, knowledge, and abilities that should be tested as training requirements. However, this section also contains some suggestions as to operational training system requirements.

As noted previously, studies on training for probabilistic forecasting indicate that knowledge of the culture or area does not by itself enable analysts to accurately anticipate future events; performance feedback using probability accuracy measures, such as calibration, is also needed. Applied research with professionals in the sociocultural domain should test this proposition. If it holds, then training systems that improve calibration of sociocultural forecasts could potentially lead to immediate gains in both the forecasting process and forecast accuracy among these experts.

Fundamental cultural values that underlie long-term changes to societies should receive greater attention in applied research and development, as they influence current events and future prospects within areas of interest. Along these lines, applied research should test the potential value of using a small set of sociocultural factors directly related to cultural change as general predictors for problems in the sociocultural sphere. Research should also test the hypothesis that analysts could be readily trained to recognize these factors, and that this would aid in preventing over-prediction and enhancing calibration of sociocultural forecasts. In addition, research should test the hypothesis that training to consider this specialized set of factors can improve understanding of why cultural change frequently does not happen or produces only temporary effects. Similarly, researchers should direct more efforts toward fine-grained analyses to understand the comparative predictive value of specific sociocultural factors typically used in current sociocultural models, and to determine new measures that yield more discriminative information. Uncovering new measures will likely be best served by precise and persistent sensing of regions of interest.

Researchers should examine the potential utility of training analysts to routinely and intuitively represent sociocultural forecast problems at the four distinct levels of analysis (ecological-historical, sociopolitical institutions, everyday social situations, and psychological adaptations) identified by Gelfand et al. (2011). Such research would test the important hypothesis that intuitive understanding of the interactions among these levels, which mutually support the status quo, can improve sociocultural forecasting accuracy, especially in terms of calibration.

Research should seek to verify whether cognitive-cultural models actually provide a framework that supports forecasting by enabling analysts to reference a cultural-insider point of view, and explore several additional hypotheses associated with the potential benefits of such models. For example, one hypothesized benefit is that the form of the model encourages thinking about specific elements of information pertinent to forecasts, and hence aids novice analysts to focus their efforts on acquiring specific cultural information relevant to their forecast problems. Another is that inclusion of quantitative estimates of cultural-idea prevalence could improve both discrimination and calibration. Applied research efforts are needed to test this claim, as well as to examine the training required to enable use of cognitive-cultural models. Such training could allow analysts to comprehend these models, as well as to create them directly from the source materials they are working with, as a way to take a cultural other's perspective.

A fair amount of applied research has sought to validate the principles underlying the approach to training analysts in cultural sensemaking, and has shown promising results. Future work should aim to develop a full CBT system based on the approach and should test its efficacy at supporting sociocultural forecasting. A lightweight e-learning system that relies on standard multimedia presentation capabilities combined with interactive exercises would likely offer a reasonable near-term solution. However, systems that incorporate interactive tutors using artificial intelligence may better identify and adapt to the wide variety of possible background knowledge and attitudes that learners bring to the cultural training environment (Woolf, 2009).

Research programs should explore training that might improve operators' conceptual understanding of various formal sociocultural models (e.g., logistic regression, agent-based models, hybrid models) and the processes by which they arrive at their predictions. Understanding the concepts underlying these models and the nature of the benefits of aggregation across models would help improve operator trust and adoption of the forecasting systems. A related line of applied research would investigate training to understand the current limits of sociocultural prediction.

Existing training efforts provide encouraging support to the idea that probability-oriented training improves specific types of sociocultural forecasts. The findings should be extended to other types of sociocultural forecasting. In addition, some programs have succeeded in integrating forecast training with forecasting support systems; further development efforts should capitalize on this initial success.

As stated at the outset, all areas of science struggle to meet the challenge of predicting events. Research and development efforts that address sociocultural sensemaking, particularly in the areas

of modeling and simulation, have made important advances in addressing this challenge in the cognitive science of culture. Future efforts to fill the gaps and test the hypotheses described here will further enhance the capability to train forecasters working in this domain, and can thereby improve predictions in operational settings.

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Section Four: Mitigating

Mitigation of behaviors in support of operational objectives

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The capabilities described in the previous sections provide a foundation for the final step in the operational cycle: mitigating the influence of adverse sociocultural behavior in the conduct of a mission. To accomplish this, commanders must develop, prioritize, execute, and measure courses of action (COAs) grounded in the social and behavioral sciences (Schmorrow, 2011). This mitigation capability builds on all the foregoing ones, and should begin the cycle anew by providing new information that updates U.S. forces' understanding of the sociocultural behavior terrain. Projecting the impact of sociocultural behavior interacting with COAs requires the use of models for robust decision making, for strategic-level sociocultural theory, for systems integration, for decision space visualization, and for agile data collection. Moreover, operating these new models and their applications requires new kinds of training.

Making robust mitigation decisions in today's complex, uncertain environment demands more than situation awareness. Decision makers must achieve *option awareness* (Pfaff, Klein, Drury, Moon, Liu, & Entezari, 2012). Option awareness level 1 means recognizing which option will yield the most satisfactory results over the widest swath of plausible futures. Therefore, this level requires an ability to compare the landscapes of plausible outcomes that may occur for each COA under a variety of conditions. Option awareness level 2 means comprehending which factors to facilitate or mitigate in order to increase the likelihood of achieving satisfactory outcomes. Hence, this level requires the ability to "drill down" to discern the sociocultural factors and environmental conditions that interact with each COA to produce better (or worse) outcomes. Finally, option awareness level 3 requires the ability to map the factors discovered through analysis back to the real world so that commanders can conceive the real-world actions needed actually to facilitate or mitigate those factors. Supporting option awareness calls for unique applications of modeling to generate multi-dimensional decision spaces, data processing to feed those models, visualization to make those decision spaces comprehensible, and training to engage in this sophisticated level of development and analysis. Each chapter in this section describes how its technology area applies to these endeavors.

The chapter on computational modeling examines a sampling of computational approaches that may facilitate COA development, analysis, and comparison, noting the potential for positive impact on decision making for mitigation. Even with the visualization, data processing, and modeling

techniques described in previous chapters, no human analyst, no matter how talented or knowledgeable, can manage the amount and complexity of the information that must be weighed for mitigation decisions. In this chapter, the authors discuss how computational modeling can relieve some of this burden, allowing decision makers to synthesize and integrate the models, knowledge, and insights from the understand, detect, and forecast phases of analysis to provide better operational awareness. Using many methods similar to the big-data analytics employed by corporations such as Amazon or Google, analysts can exploit this wealth of sociocultural knowledge to support decision making and determine the most robust COA in many critical situations.

Because decision making for mitigation relies so heavily on computational modeling, data processing for the mitigation capability must support interfaces among disparate models – interfaces so complicated that their design is itself an act of modeling. Consequently, the chapter on data processing centers on the representation of the data that are input, output, and traded between models and the interfaces among the models that arrange how those data are traded and are translated into the languages of the different models. Applied to COA analysis in sociocultural scenarios, data representations span strategy and narratives. They also include co-evolutionary model interfaces, game theoretical arrangements of disparate models, and interfaces that preserve uncertainty. This chapter first presents an example of an irregular warfare battlespace, and then discusses state-of-the-art social data representations and interfaces of social data for COA analysis of irregular warfare, giving examples of their value in representing social phenomena.

At its best, effective visualization can lead to a deeper understanding of COA robustness, resulting in better outcomes in more situations. The chapter on visualization covers the underpinnings of effectively using visualization to help decision makers deeply comprehend their options. The author discusses the research to date in this area and promising directions for future research in this nascent area of using interactive visualization to help compare and contrast COAs. Most visualization tools today present situation awareness data, leaving the burden on the user to extrapolate from the details of a situation to decide on a good COA. This chapter describes new interactive visualization tools that support each level of option awareness, giving decision makers a much broader and deeper view of their options. If the visualization enables option awareness level 1, decision makers will more rapidly see and understand the comparative robustness of their options. If the visualization enables option awareness level 2, the decision makers will comprehend the key trade-offs between those options and the factors that make one option more robust than another. Building on levels 1 and 2, decision makers who achieve option awareness level 3 can conceive new, more effective options based on a deep understanding of relative robustness and the factors driving that robustness.

As additional technologies to support sociocultural mitigation improve and are deployed, more operational users will need training on how to use these tools, data, and analytics appropriately and optimally to mitigate and shape potential futures. In contrast, limited time, tools, and capacity currently restrict the number of prospective COAs for mitigation that operational planners can generate and assess, because the processes implemented today are manually intensive and seldom integrated (computationally) with sociocultural knowledge. The quality and kinds of information that new technologies make available to users and the potential utility of this content will begin to

blur the traditional "lanes" separating current career fields such as intelligence, operations research, and operational planning. This, in turn, will require innovation in training to prepare users to effectively recognize and leverage relevant content in order to analyze COAs for mitigation. For example, training on model interpretation, typically concentrated in a particular career field such as operations research, must be expanded to ensure all operational users can use emerging mitigation technology rapidly and properly. The chapter on training focuses on defining the skills (abilities necessary to perform the task) and knowledge (facts, concepts, and principles needed to perform the task) for mitigation decision making in order to establish new guidelines for training. An initial analysis of the functional tasks involved in mitigation highlights several key training considerations, such as appropriate objectives and ideal training formats (e.g., computer-based training, classroom, or exercise).

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13 Data interfaces for input, output, and translation between models[1]

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1. Introduction

Data processing for course of action (COA) analysis of irregular warfare (IW) scenarios differs from COA analysis of conventional warfare scenarios for many of the same reasons that social science differs from physics. A significant difference is that physics models are models of things, while social models are models of modelers because all people model their world. IW focuses on the reactions of a population of these human modelers—reactions that, unlike physics-based outcomes, are neither straightforward nor equation-based. This distinction encapsulates the challenge of processing sociocultural data. Sociocultural data processing requires interfaces between disparate models—interfaces so complicated that designing them is itself an act of modeling. Physics models, by contrast, typically implement Newtonian-based, validated data that can be held in limited repositories and require no translation because the models rely on shared and accepted concepts.

IW modeling involves reproducing a series of moves and countermoves that antagonists might use to convince populations to model and act upon events in one way and not another. How agents—whether human or software agents—react to IW moves results from their interpretations, or the way that they model the moves. Information operations (IO) present narratives to counter terrorist narratives; Civil Military Operations (CMO) embody these counternarratives. Both terrorist and CMO narratives are processed by minds that create interpretive models to determine which narratives make sense to them. A population's reaction to IW, IO, or CMO is represented by the computation in and the interfacing of models in individual agents' "minds."

Consequently, data processing for mitigation encompasses the representation of the data input, output, and trades between models, the interfaces between the models that arrange how those data are traded, and the ways in which the data are translated into the different languages of the different models. Applied to COA analysis in sociocultural scenarios, data representations include representations of strategy and narratives. They also include coevolutionary model interfaces, game theoretical arrangements of disparate models, and interfaces that preserve uncertainty.

[1] Approved for Public Release; Distribution Unlimited. Case Number 14-2487

This chapter uses the film *The Battle of Algiers* as an example to provide context for the IW battlespace. It then discusses state-of-the-art social data representations and interfaces among social models for COA analysis of IW, giving examples of their value in the representation of social phenomena.

2. IW Strategic Scenario

To design data representations for COA analysis with sociocultural models, we must first understand how the models are used. In the context of this chapter, the moves and countermoves of IW form the crux of what sociocultural COA analysis examines. These moves and countermoves represent the antagonists' attempts to change the population's perceptions. To anchor the discussion of sociocultural data for COA analysis, we present a synopsis of the movie *The Battle of Algiers*, produced and written by the actual insurgents and shown in the Pentagon as an archetypal IW scenario in which an insurgent group used IW tactics to make the transition from unpopular to victorious (Solinas, Yacef, Pontecorvo, Musu, Haggiag, & Martin, 1976).

In 1954, the French suffered defeat at Dien Bien Phu, Vietnam, prompting French withdrawal from its Indochinese colonies. The French now appeared vulnerable, and Arab resistance elements in Algeria believed that the French would not want to engage in another colonial war. However, the French considered Algeria fully a part of France and were determined to counter any rebellion. Even so, the French public was susceptible to narratives that highlighted the political and economic discrimination that indigenous Algerians suffered. The regime deprived 10 million indigenous Arabs in Algeria of political rights, and almost all of the economy was in the hands of one million French Algerians, who enjoyed better houses and schools than the Arabs. Note that the points of vulnerability of the French, and the sources of strength for the Arabs, were cognitive: the war-weariness of the European French, the European French conviction that Algeria was an integral part of France, and the potential for the indigenous Algerians to perceive injustice were all ideas critical to motivating the popular will. IW simulations should capture such ideas, how they spread, and how they motivate IW actions.

The Algerian insurgency, known as the National Liberation Front (FLN), argued that the French Algerians did not respect their culture and incited decadent behavior such as prostitution and drunkenness. The FLN therefore campaigned to purify Algeria, imposing their own death sentences on the population for behavior that contradicted Muslim values. The movement assumed other functions of government as well, such as performing wedding ceremonies. The FLN strategy was to win the respect and support of the people and thereby secure hideouts for themselves. Ethnic violence between the French and Arab Algerians included an uprising in 1945 in which 90 French Algerians were killed, followed by a French massacre of over 40,000 Arabs. Many Algerian Arab insurgents cited this massacre as a factor in their decision to join a terrorist group. Despite this history, in 1954 every newspaper in Algeria, including the communist papers, favored elimination of the FLN. Note that the massacre constituted evidence that countered the newspapers' anti-insurgency narrative, while the contrast between French behavior and Muslim values supported the narrative that insurgents who suppressed these behaviors deserved respect.

When the French guillotined FLN leaders in 1954, the FLN complained that they were being treated as criminals rather than combatants, and organized an insurrection against the Algerian police. The police reacted by instituting curfews, checkpoints, and searches of Arabs, sometimes violating cultural restrictions on searching women. The French Algerians, together with members of the police, also bombed the Kasbah, a concentrated ethnic Arab section of Algiers, killing 75 Arab civilians. The Arab populace rushed out to demonstrate in the streets, but the FLN stopped the demonstrations, telling the people that they would be slaughtered and that the FLN would avenge their compatriots. The FLN did this because they feared that widespread killing would intimidate the people whom they hoped to rally to their side. Note that protecting the populace and avenging them supported the narrative of the FLN's legitimacy as an ally and prevented emergence of a discouraging narrative of the hopelessness of standing up to the French.

In 1956, the FLN avenged the Kasbah bombing by launching a simultaneous attack on three French civilian targets, killing many French Algerians. Some French Algerians responded by targeting innocent Arabs and even Arab children. The government of Algiers turned the situation over to the French army.

In 1957, the FLN coordinated an eight-day general strike to gain the attention and support of the international community, specifically the United Nations (UN). Despite widespread support within Algeria, the strike had little impact on the UN because the French army broke the strike in a day by forcing people out of their homes, opening the shops themselves, and compelling owners to open their stores when they tried to protect their goods. However, the government's aggressive response served to anger the Arab population further. The FLN's terrorist actions and the French retaliation led more and more people to believe the narrative that the French were the enemies of indigenous Algerians. The insurgents successfully turned the Algerian Arabs and the international community against the French government by inciting harsh reactions. At the same time they insulated the people and themselves from intimidation by timing demonstrations and strikes so that supporters would feel strength in numbers and not fear reprisal.

Both sides paid attention to the perceptions of the people and the international community by following unwritten rules of legitimate action, evidenced by their seeking to justify their actions. For instance, the insurgents sought favorable opinions by advancing the theme that the French government had crossed the line by harming civilians. The insurgents also presented the Algerian government with "damned if you do, damned if you don't" situations, where the cure had the side effect of causing more damage. For instance, by pressing the government to end checkpoints the insurgents would benefit no matter how the government responded: they would reap direct gains if the checkpoints ceased, but would obtain additional popular support by making claims about humiliating searches and violations of custom if the checkpoints continued.

Although the local population generally favored the insurgents and sheltered them, the Algerian government and the French army achieved short-term tactical success by arresting and often eliminating FLN members. The FLN instructed its adherents to remain silent for 24 hours if they were captured, which would render their knowledge of safe houses useless. To counter these instructions, the French army used brutal torture techniques to obtain information in the few hours

during which it was still useful. However, the army weakened its own cause by torturing some persons who were not insurgents. This further deepened the belief that the French were the enemy of the indigenous Algerians. Over time, the Arab population and the French press learned about the torture, giving rise to an even larger insurgency in 1960. The result was a strategic defeat for the French-supported Algerian government, even though the French had "won the battle" by eliminating nearly all insurgents. The strategic defeat caused by the Algerian populace's changing beliefs ultimately led to the end of French control in Algeria.

3. Representing IW Strategic Data

In the *Battle of Algiers* scenario, insurgent moves embodied strategies to make the French act in a manner that advanced the narrative of "the French as oppressors." Although the French lacked a counternarrative, modern doctrine combines IO with CMO to support narratives reinforcing the legitimacy of the host nation or friendly forces. To represent insurgent and coalition force COAs for an IW scenario, modelers must represent the narratives, the population's reactions to the narratives, and events surrounding the narratives. Additionally, they must capture the insurgents' mental model of the population and the coalition forces' mental model of the population, if applicable, as well as the reactions of insurgents and coalition forces to each other. Steve Corman's project on Identifying Terrorist Narratives and Counter-Narratives (ITNC) at the Center for Strategic Communication and Arizona State University, John Horgan's project on Competitive Adaptation in Terrorist Networks (CATNet) at Pennsylvania State University (Horgan, Horne, Vining, Carley, Bigrigg, Bloom, & Braddock, 2011), and Jerzy Rozenblit's Asymmetric Threat Response And Analysis Program (ATRAP) at the University of Arizona (Mitchell, Craw, & Ten Eyck, 2011) present innovative ways to represent strategic ideological moves and countermoves.

According to narrative paradigm theory, people think in stories (or frames) and interpret events through these frames. Corman, Ruston, & Fisk (2012) developed a method to extract frames from text that represent cultural narratives and cluster them into groups of "master narratives" that contain archetypes. Corman uses the Natural Language Processing (NLP) technique to identify similar stories and concepts in these stories as general archetypes, and then counts how often these archetypes appear in news stories to obtain a measure of belief of the host nation. Corman examines the archetypal master narratives for evidence that friendly forces can show the host nation population to discredit terrorist narratives, on the assumption that the average person can be convinced with logical argument. He also examines possible narratives that the host nation could adopt to counter the terrorist narrative, thus helping the host nation population to interpret U.S. actions as we wish.

In the Algiers example, the host population initially internalized a narrative that they were French citizens, accepting blame for the massacre of their citizens following their 1945 uprising. However, that framing of the situation did not sit well with the indigenous Algerians: because the narrative minimized the disproportion of the response it caused cognitive dissonance. The insurgents took advantage of this dissonance by offering the population a way to resolve it cognitively, which also put the FLN in power. The insurgents' counter-narrative focused on injustice, framing the situation as a breach of contract, as well as one of moral decadence, if Algeria remained under French rule.

This theme of unjust treatment became a master narrative in the Muslim world that has persisted through the Arab Spring of 2010. The French offered only the counternarrative that individuals who joined the resistance would be tortured and the population massacred. This narrative of fear caused revulsion not only among the indigenous population but also in France proper, and was not consonant with either party's value system. The French resolved the dissonance by withdrawing their forces and granting independence to Algeria.

In Corman's unique formalization of narratives, an analyst starts with free text such as news articles, parsed with resource description framework (rdf) triplets of subject, verb, and object. The analyst identifies stories in the text, creating graphs that represent the stories. After manually dissecting many articles in this manner, the analyst clusters individual graphs to obtain an objective "story distance" measure. The analyst measures story distance by taking all triplets in one story and comparing them to all triplets in another story, scoring the same noun or its synonym with its inverse document frequency (IDF), a measure of the noun's uniqueness. If the verb is the same or a synonym (as determined by the verbNet thesaurus) its IDF score is added to the triplet distance score. The sum of the added IDF scores of all the triplets determines the similarity of the entire story to another story. Then, the analyst assumes that close stories adhere to the same general archetype, and extracts the similar nouns and verbs to make up a general story pattern and objectively measure the frequency of that pattern in news articles as a measure of belief. For example, this technique could enable analysts to measure the frequency of the master narrative of injustice in the Algerian and French press during the battle of Algiers, mapping the population's beliefs over time.

The ability to model IO, including IO content, the impact of IO on the population, and the reasons a population accepts (or does not accept) IO, remains the largest gap in IW modeling. Analysts can use Corman's objective formalization of stories as an indicator of a story's recurrence as well as an explanation of why a message is accepted or not. Modelers can use this formalization to represent the cognitions of host nation agents in simulation models, and to feed these cognitions into the agents' "minds" directly from news articles. This technique not only allows modelers to enter data into simulations and to compare simulation data against real world data for validation, but also facilitates a representation of cognition that enables models to compute the acceptance or rejection of messages. Corman's method lends validity to studies precisely because it addresses the causation behind message acceptance as it exists in cognition.

By contrast, Horgan's research describes terrorists' evolving behavior throughout a conflict or throughout the terrorist's career. Horgan is a widely acclaimed expert on terrorism; his CATNet project shapes the detailed interviews and field work he conducted into a story of competitive adaption, or coevolution, between insurgencies and government. Horgan defines competitive adaptation as the ability to learn from an adversary and gain a variety of skills in order to overcome the enemy. Horgan's methodology involves detailed, structured interviews to capture how individual terrorists learn and change throughout their careers, asking questions about what they learn from the governments they are fighting. His studies revealed that terrorists act in response to their government enemies: with every new initiative by the government, the terrorists find a new strategy to circumvent the government and enforce their will on the people. Horgan's interviews

capture the coevolutionary dynamics of insurgencies in the Military Information Support Operations (MISO) moves and countermoves that are central to terrorist activities. The coevolutionary information that Horgan gathered can serve as excellent training data to tune coevolutionary agent models as well as test data against which to validate the models.

While Corman represents the narrative in text, and Horgan represents the coevolution of conflict in structured interviews, Rozenblit represents the coevolution of conflict in text. Rozenblit led development of ATRAP, a toolkit that aids intelligence analysts to find and interpret patterns in free text that could represent enemy COAs. ATRAP combines genetic algorithms, game theory, and NLP to give analysts an automated filter for documents that together create alerts and situation awareness of possible enemy actions. The system finds entities and links in text that form patterns that an analyst can mark as an indicator. The analyst can then build a threat template by stringing together indicators in parallel and in sequence to describe enemy tactics, techniques, and procedures (TTPs) or any COA.

In the context of the Algerian example, the threat template might string together the three indicators “money transfer”, “to organization”, and “related to location of interest” in parallel with the three indicators “money transfer”, “to organization”, and “related to equipment of interest.” The French forces could have applied such a threat template to unstructured text in messages, such as terrorist interrogation reports or human intelligence (HUMINT) reports on *hawala* exchanges, with a location of interest such as “Kasbah” and equipment of interest such as “explosives.” If an ATRAP template identified the money transfer as a gold transaction over $1,000, it could indicate purchase of an explosive.

ATRAP's innovation lies in the way templates model plausible changes in terrorist TTPs. ATRAP first uses a genetic algorithm to find new patterns that resemble existing patterns in the text corpus. ATRAP then applies game theory to model how this new template, as a COA, would play out against existing defenses in a coevolutionary dialectic with counter-tactics. Staying with the Algerian example, if the insurgents had used game theory to model the new tactic of simultaneous bombing, they might have predicted that demonstrations would occur if the French employed a kinetic response to counter a simultaneous bombing. The French could counter the demonstrations with an even larger kinetic response, which might discourage the population from supporting the insurgency. To adapt their strategies, the insurgents chose to discourage the reactive demonstrations.

ATRAP could be further enhanced to include identification of terrorist and friendly narratives in data and associated actions such as CMO responses to insurgent actions. To do so, ATRAP would either have to be augmented to find indicators of narratives, or work in concert with other programs that identify terrorist narratives and counternarratives, such as Corman's ITNC. Once modelers have formalized the representation of narratives and COA templates and extracted them from the text, they become available for models to ingest as “training” data or as “testing” data to validate the model.

4. Coevolutionary Integration of Models for COA Analysis of Social Institutions

The arrangement and integration of models is another dimension in data processing for COA analysis. Model integration, because it involves interactions between disparate models through data, is a task for data processing rather than for modeling. An autonomous agent, and the way a cognitive autonomous agent models its environment, could be viewed as a complete model in itself, while the interface between agents constitutes a model integration scheme.

Coevolutionary integration of models has particular importance in COA analysis. Coevolution is a model integration scheme that can compute a population's reaction by integrating individual agents, each of which uses an autonomous machine learning algorithm for maximizing utility—that is, for best achieving goals. Such agents are autonomous because they calculate for themselves how to perceive and act to increase their utility, and do so in a way that makes sense in their individual situation. Coevolving agents determine how to perceive and act by using a method of induction, such as a neural network, genetic algorithm, Bayesian network, reinforcement learning algorithm, or even a cognitive architecture (Alpaydin, 2009; Mitchell, 1998; Sun, 2008). Inductive methods compute how an agent should perceive and act through trial and error iterations of perceptions and actions based on how these perceptions and actions affect utility. The important aspect of model integration is that the agents exert coevolutionary pressure on each other, meaning that they change each other's utility values as they act upon what they learn. Thus, although agents may have static overall goals such as "survival," the most effective subgoals to achieve these goals may change.

Integrating individual agent "minds" so that they influence each other's perceptions is a good way to model IO COAs because the purpose of an IO model is to explore why a particular belief would make sense to agents, whether human or software, in their individual circumstances. Models of IO that do not walk through sensemaking, such as homophily models based solely on copying agent neighbors, cannot explain why some IO messages are not copied, that is, why they failed to influence the intended audience, and therefore cannot test COAs. Coevolving agents are not so dependent upon each other as to be empty of thought, like homophily-based agents, nor are they fully independent thinkers that have no effect on each other: rather, they are autonomous networked beings, each of whom/which influences what makes sense to the other.

The integration scheme between individual models of thinking agents (their external interface) represents the agent's social world. Sociocultural modeling focuses on what happens in the interface: the connection between the agents' minds (in other words, their network). Understanding social behavior equates to understanding institutions. Human institutions are social because they are based on human agent's knowledge of how other human agents will react to their behaviors. For example, bribery is social because people would not offer bribes if they did not have confidence that the bribe would be accepted, or at least that they would not go to jail because of the bribe. To achieve their goals, agents learn corresponding behaviors, such as to bribe and to accept a bribe. As these behaviors become expected, they change the utility of the agent behaviors, so that bribing increases utility only if the bribes are accepted. As these behaviors become commonplace, they become institutions.

The *Battle of Algiers* scenario shows the alignment of goals into acceptable behaviors that rely upon established institutions, such as rules about actions that merit support. For example, the strike that the FLN initiated was not large enough to garner support from the UN, but the French suppression of the strike was violent enough to be distasteful to the European French and reduce their support of the war effort.

The interdependence of behaviors, to include interlocking and corresponding behaviors, causes societies to develop into distinct types in which not every possible combination is possible. Behavioral dependency makes social behaviors self-reinforcing, causing virtuous or vicious cycles. COA analysis of an entire society, therefore, amounts to the study of when society tips from one self-reinforcing set of behaviors to another, and IO COA analysis becomes the study of why a paradigm shifts from one way of viewing the world to another. That paradigm shift in viewpoint is critical to the behavioral change.

The Nexus Cognitive Agent Program (Nexus), created at the Office of the Secretary of Defense (OSD), modeled corruption and popular support in OSD's first IW Analytical Baseline, the Africa Study (Duong, 2012). In Nexus, corruption is modeled as a system of interlocking behaviors that agents learn to execute (or not) depending on how the behaviors affect utility. Utility in Nexus is defined by cultural values. For example, in the *Battle of Algiers* scenario, both the general population and the insurgents had cultural goals such as eliminating prostitution and alcohol consumption. In the Africa Study corruption scenario, software agents represented human individuals and utility was defined by African tribal cultural values. For example, a tribesman from a matrilocal tribe may care that his maternal grandmother has bought enough food in the market in the past year to sustain her health. Choices to give and receive bribes only indirectly affect utility, but indirectness is important because we can effectively explore whether bribery is effective or not under a variety of circumstances. If our simulation could produce no other outcome—that is, if bribing always generated positive outcomes and the optimizing agent has no recourse but to bribe—then we cannot report to senior leadership that we have studied bribing with scientific validity.

In the Africa Study corruption scenario, Nexus agents possessed a strategy of behaviors, telling them to bribe, accept bribes, steal, or tolerate stealing, along with a variety of network choice behaviors. Each strategy was a chromosome in a Bayesian Optimization Algorithm (BOA). Each agent had its own private BOA with 20 strategies, defined as a combination of behaviors, and executed each strategy for one year. The strategies were ranked by utility of the agents' dependents, for example, the maternal relatives of matrilocal agents. The 10 best strategies were retained and Nexus then created ten more new strategies with the same statistical properties as the ten best.

One particular analysis that can be conducted utilizing the Nexus tools involves testing the effect of transparency programs versus higher judicial penalties on the society to determine which COAs will tip the society from corrupt to noncorrupt states. For example, analysts can test for a reduction of bribery transactions between agents, such that agents no longer expect to receive bribes from

other agents or feel obligated to offer them, or examine other goals that the COAs attempt to affect.

In the Nexus Africa Study's popular support scenario (Marling, Duong, Sheldon, Stephens, Murphy, Johnson, & Ottenberg, 2008), every agent maintained a neural network with which to induce popular support and determine whom to credit and whom to blame for actions based on consistency theories in social psychology. The model implemented Festinger's cognitive dissonance theory (Festinger, 1957), Heider's balance theory (Heider, 1946), and Fischer's narrative paradigm (Fischer, 1984). Nexus assigns each agent a constraint satisfaction neural network, specifically, a Boltzmann machine, to represent the mind. In this network other agents tend to be supported if they treat the agent well and support the agent's "friends," and tend not to be supported if they treat the agent poorly or do not support the agent's friends. Historical actions and a network of support all contribute to an agent "schema" of support. That schema consists of a set of reinforcing facts that cause an agent to polarize friends and enemies, and perhaps to blame its enemies for more than they have done while perhaps supporting its friends more than they deserve. Support relations, such as coalitions, that link the agents arise from these schemata in the form of public declarations of support; because they are self-reinforcing they tend to tip the society between states. The schema enables COA analysis of popular support, such as how coalitions change as a result of exogenous interventions. The coevolutionary integration scheme between autonomous agent models is critical to the COA analysis, because popular support takes the form of data traded between the models, and coevolution of this data represents how individual agents change each other's minds.

5. Game Theoretical Integration of Models for COA Analysis of Strategic Moves and Countermoves

Recall that not only software agents but also their cognitions about their environment are individual models. Models can represent a strategist agent's situation awareness, and can be executed in a way that represents each side's mental model of the enemy and of the host population. Thus models can be integrated in a game-theoretical manner for analysis of strategic moves and countermoves. In this way they can represent a mental model, or "what if he thinks X…" scenario, even if they were designed as models of the environment. For example, the eXtensible Behavioral Model integration framework (XBM) project led by Impact Computing (2013) is an open source tool that enables the representation of a strategist agent's situation awareness by running any models (not just cognitive models) as though they were the strategists' mental models.

XBM runs models in innovative strategic combinations with each other for COA analysis. Specifically, it supports the concept of *strategic data farming*, a variation of data farming that utilizes game trees to detect best COAs during scenario runs (Duong, Brown, Schubert, McDonald, Makovoz, & Singer, 2010). Data farming is a form of COA analysis by testing parameter sensitivity through a very large number of model execution runs. One way to test COAs with computer simulations is to trace which inputs, such as IW actions, lead to which outputs, such as popular support. Again using the *Battle of Algiers* scenario, inputs for the French commanders could be kinetic strategies to eliminate the insurgents through checkpoints, curfews, and harsh treatment,

while outputs of interest would include estimates of popular support among the indigenous Algerians and the European French. Data farming is complicated because the large number of parameters in sociocultural simulations typically precludes testing every parameter in combination with all the others to see what combinations of inputs lead to what outputs. Testing parameters in combination could require billions and billions of simulation runs; a stochastic simulation would demand an order of magnitude more runs to cover the space of possibilities.

Data farming covers the parameters as evenly as possible by applying methods such as Cioppa's "orthogonal Latin hypercubes," which optimize parameter coverage on a simulation treated as a black box (Cioppa & Lucas, 2007). Strategic data farming has a different focus: rather than examining all possible outputs from the simulation, it performs risk-based COA analysis by sampling the output space in proportion to likelihood. For example, in the Algerian scenario, kinetic input moves of the French government would usually correspond to input moves of the insurgents such as strikes. Because simulation parameters are not in fact orthogonal, strategic data farming inputs parameters proportionately to generate a proportional output space.

Using strategic data farming, XBM can also represent deception, a concept central to IO campaigns. In XBM, an analyst may execute a model scenario depicting the red side's concept of the blue side's concept of the battlefield. One example of deception is the IW tactic of trying to incite trouble so that the other side seems brutal and receives the blame of the population. This tactic appeared in the Algiers example when the insurgents bombed French citizens, eliciting a harsh reaction from the French police. XBM could execute a model that represents the indigenous Algerian population's reaction to French kinetic and nonkinetic moves as the insurgents' cognition regarding the consequences of their own actions meant to incite the French. Executing these coexisting situation awarenesses and resultant behaviors results in a COA analysis based on strategic moves and countermoves.

Analysts at the U.S. Army Training and Doctrine Command Analysis Center (TRAC) applied strategic data farming to an IW IO scenario using XBM and Nexus. The research evaluated moves, countermoves, and strategies from TRAC's tactical wargame to determine the best COAs under certain conditions. The research also provided insight into the population's attitude toward the host nation and insurgents, and helped identify tipping points where the population may shift allegiance.

XBM performs dynamic moves to achieve agent objectives by implementing the following three capabilities: (1) assessing indicators that measure how far agents are from their goals at specific time intervals, (2) saving and precisely restoring the simulation state (checkpoint/restart), and (3) implementing moves. XBM defines player strategies, and players' perceptions of other players' strategies, in advance. In strategic data farming, a strategy consists of the following elements from the Military Decision Making Process (MDMP):

- Decision points – conditions under which a change of Concept of Operations (CONOPS) is to be considered
- Branches and sequels – doctrinal guidelines that constrain and define possible moves

- Goal states – ultimate objectives
- Subgoal states – proximate short-term objectives

XBM maintains "ground truth" that represents reality as opposed to any particular player's view of reality. When a player's decision point has triggered and the player must choose among doctrinal moves, the simulation is executed from the viewpoint of the decider (decision maker). In other words, the simulation executes the decider's idea of the other players' points of view as the decider looks ahead (mental model) to what might happen. If perception and deception are excluded only one model is needed, because blue's view of red's plans and what red sees are assumed to be correct and vice versa.

When the decider reaches a decision point, or believes that other players have reached a decision point, the simulation branches (along the game tree) according to the top *n* moves of that player's strategy. Other player's moves are translated back to the decider's simulation, which represents the decider's ground truth. This pattern recurs until a certain number of decision points have been reached, and then XBM judges each separate simulation according to the decider's idea of the other player's goals. XBM sends the score of the simulation back up the mental model game tree, assuming each player selects actions that lead to the most favored condition. The decider then picks its next move with the assumption that each player is optimizing its goal at every decision point. All players decide their next moves in the same manner, and then the ground truth simulation advances to the next decision point.

Figure 1 illustrates a small portion of a game tree in which blue looks ahead for six decision points. Ratings are shown for each simulation state from the bottom of the tree (not shown).

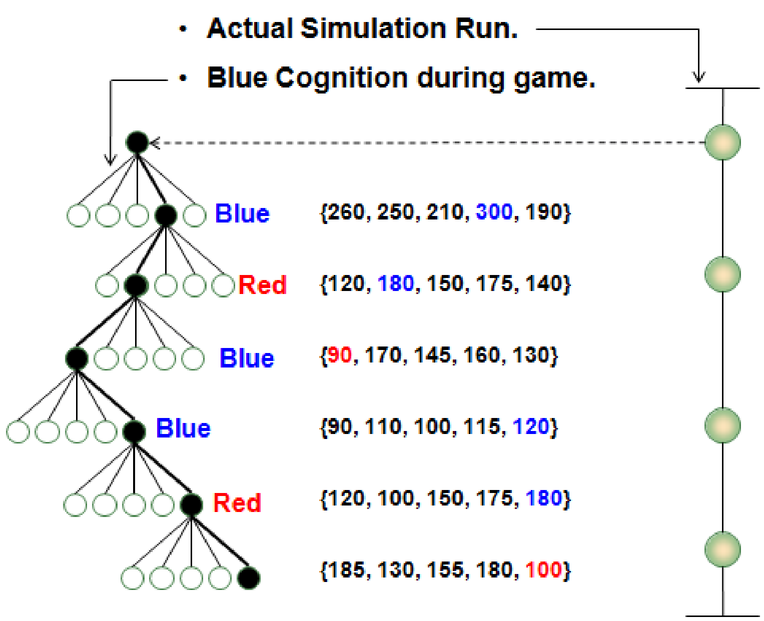


Figure 1. One decision point is reached in a simulation, causing blue to examine six decision points and choose a COA according to its CONOPS.

Figure 2 illustrates an example run of the Nexus model. In the Africa Study, Nexus modeled and measured intergroup support levels. Nexus represented a “group mind” for each tribe and computed support levels based on past historical events and support networks. The study measures intergroup/alliance strength by executing stochastic Nexus ten times. If a group mind was positive about another group in every case, then the alliance was deemed solid. If a group mind was positive about another group half the time and negative half the time the alliance was deemed tippable.

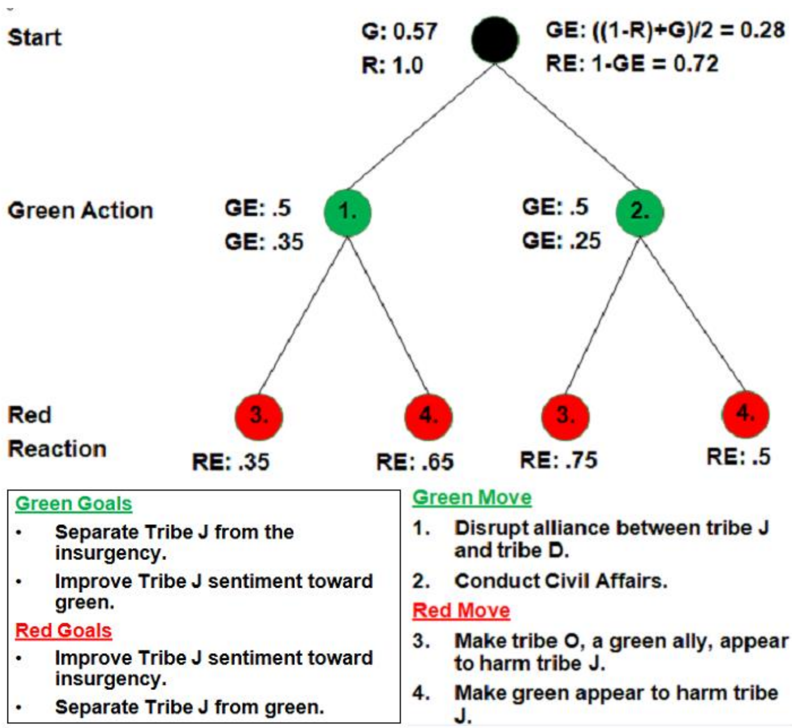


Figure 2. Goals, doctrinal moves, and evaluation function (GE and RE) of a Nexus strategic data farming walkthrough.

In this scenario, green represents the host nation government actions and red represents insurgent actions. Both green and red focused their attention on the opinion of Tribe J, the main tribe from which the insurgency recruited its members. All the people of Tribe J initially had positive views of the insurgents, even though 57% of Tribe J also had positive attitudes towards the green government.

Green wanted to act in the region because its popular support had waned. The objective function was to form a more solid alliance with one’s group and a more solid opposition with the opponent.

Green’s evaluation function was: GE= ((the ratio of times green’s support node was illuminated in Tribe J’s brain) + (the ratio of times red’s support node was illuminated in Tribe J’s brain))/2. Red’s

evaluation function was: RE = 1– GE. An increase or decrease in the evaluation function served as the decision point. Fully executing the single mind of Tribe J in Nexus with no moves, to get a baseline of what would happen in the simulation had no party intervened, resulted in a tight alliance between Tribes J and D, and a GE score of about .28.

Assume green's strategy involves a choice of either performing positive civil affairs actions or trying to disrupt the alliance between Tribes J and D by causing ethnic tension (for example, having a Tribe J member provoke an attack by Tribe D members, filming it, and broadcasting it to Tribe J members). When green assesses these moves in isolation, both increase GE to 0.5. To differentiate between the two, green must look at the vulnerabilities its actions may have created for red retaliation. Say that the red strategy only includes making others look bad (for example, by provoking green into acts of violence against Tribe J, and by inciting ethnic tensions between Tribe J and a green ally, Tribe O). If green only performs civil affair actions, inciting tension between Tribe J and Tribe O causes RE to reach 0.75. Green acts of violence against Tribe J result in an RE score of 0.5. Thus, since red would choose to incite tension (because it would cause more damage), the true value of the civil affairs action to green is GE = 1 – 0.75 = 0.25.

On the other hand, if green first causes ethnic tension with Tribe D and red retaliates by causing ethnic tension with Tribe O, then RE = 0.35, and if red retaliates by inciting acts of violence by green against Tribe J, RE = 0.65. Thus, in this case, red would again choose to incite acts of violence against Tribe J, the action with the strongest effect. Apparently, if green incites ethnic tensions first, it is protected from the effects of red actions later. Accordingly, the value of inciting ethnic tensions to green is GE = 1 – 0.35 = 0.65. Since 0.65 is greater than the present value of 0.28, it is to green's advantage to take this action, given the strategy and goals of both sides.

Another model that integrates agent minds that interact and think through consequences of their behavior is Senturion, a proprietary model of Sentia, Inc. (Kugler & Abdollahian, 2013). Senturion simulates the political bargaining process on the basis of two economic theories: median voter theory and expected utility (EU) theory. Median voter theory is a technique for predicting the stance that stakeholders (for example, a political candidate) might take on an issue in order to win the most support. Senturion uses game theory and the assumption that the candidate sells out his actual position in order to win votes, where the winning position is the median.

Senturion uses EU theory to incorporate a form of perception and cognitive bias – risk aversion – into this purely rational game theory technique. Instead of assuming that the politician will do anything to win, Senturion calls the selling out of one's beliefs "risk aversion" and represents the tradeoff between that and retaining one's beliefs as "risk acceptance." Senturion identifies the stakeholders near the median issue stance as risk averse and likely to give in, while stakeholders far from the median accept risk and are unlikely to move far from their positions.

Senturion uses parameters that include the salience of an issue to a stakeholder, and stakeholder influence, to calculate a "weighted median." In each iteration of Senturion, agents make proposals to all other agents regarding position change, and every agent then chooses one proposal and moves toward it. In deciding what proposal to accept agents consider how much influence a

stakeholder wields and how important the issue is to the stakeholder. Additionally, a risk-averse decider magnifies how much power another stakeholder has, while a risk-acceptant decider disregards another stakeholder's power. Agents assess where they would land if they took an offer, and then choose the offer that causes them to move as little as possible from their present position.

EU is well vetted and accepted by the modeling community. It combines the two most important components of decision making: rationality and bias. Thus, EU captures the tradeoff between the idealist's adherence to principle and the practical bow to social pressure that permeates politics.

Senturion is the best current model of political bargaining, and is highly useful for the study of IW. In the Africa Study, Senturion represented popular support of the host nation as the issue about which the stakeholders should arrive at consensus. In the *Battle of Algiers* scenario this would be the equivalent of modeling the insurgents, the Algerian indigenous population, the French Algerians, and the European French as stakeholders, inserting kinetic and nonkinetic COAs for each, and computing their compromises based on their relative power.

6. Preserving Uncertainty for Risk-based COA Analysis

New data processing methodologies for COA analysis include representations of narratives, COA templates, and elements of the MDMP. They also include methods for integrating models to compute social network behaviors to test interventions, as well as the strategic interactions of IW. However, one especially important methodology that research must advance is tracking uncertainty for risk-based COA analysis. In conventional warfare analysis, uncertainty stems from a few random variates from distributions inside physics-based models. IW analysis must take into account uncertainty in data, uncertainty on the correctness of social theory, uncertainty on the correctness of the representation, uncertainty in the way to translate data between disparate models and data created for different purposes, and even intrinsic uncertainties of human behavior.

Innovative methodologies help track these uncertainties. For example, researchers could mitigate the uncertainty about social theory by testing the theories underlying different models in proportion to their reliability and testing strategies for robustness against all theories. Because there are so many possibilities, sociocultural analysis requires multiple models that depend on integration frameworks to track the uncertainty. Integration frameworks such as Oz, Global Information Network Architecture (GINA), XBM, and SIMmiddleware translate between models using ontologies in hub-and-spoke arrangements. An ontology is a grouping of data into the language of a domain, along with the rules for grouping the data. Ontologies are used for translation because they define their terms precisely. A probabilistic ontology additionally represents uncertainty in knowledge about how data are grouped and how they should be translated by combining crisp ontological logic with Bayesian inference.

For the TRAC tactical wargame, SIMmiddleware integrated hub, spoke, and mediation probabilistic ontologies to support analysis (Duong & Bladon, 2012). These ontologies tracked the uncertainty of

data translation so that the results kept track of the likelihood of a particular outcome. The uncertainties within the ontologies were combined using rule-based systems. For example, the translation between the Cultural Geography (CG) model (one of the tactical wargame models) and the hub model required probabilistic translation. Specifically, analysts created a one-to-many mapping of CG moves to hub model moves that SIMmiddleware implemented using probabilistic ontologies. Probabilistic ontologies were also used to assess crisp rules to fire decision points based on popular support indicators. Probabilistic ontologies such as Bayes Owl combine probabilistic and crisp logic (Ding, Peng, & Pan, 2004).

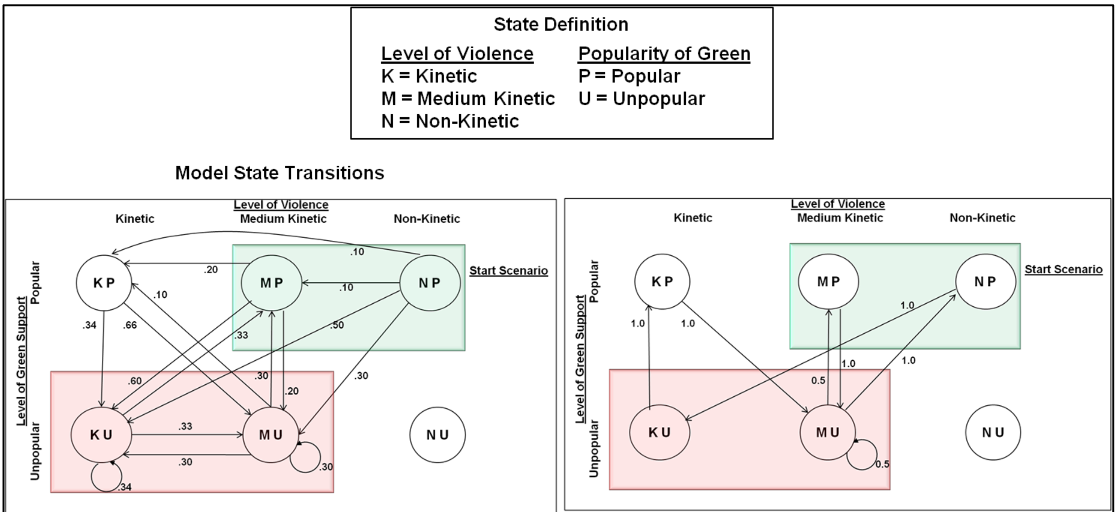
XBM provides a way to take data credibility into account in a proportionate output using a mixing function. A mixing function draws proportionately from input data sets according to their reliability, using XBM's probabilistic ontology, ProbOnt. SIMmiddleware provides a way to track these forms of uncertainty, data pedigree, social models, and model translation, so as to output the results of multiple runs proportionately into a Markov process. A Markov process, a node-and-link graphical model that displays the probability of going from one state to another, describes the state space (all possible states) probabilistically. The Markov process can be used to analyze likely tipping points. For example, to measure the effectiveness of an action, the process can calculate the likelihood of reaching any state from the point of the action and can show whether selected actions can achieve desired goal states. The process can also analyze actions that drive the system to states in which the goal is more easily attainable.

7. Data Processing Implications of Validation of COA Analyses

Although IW scenarios in simulation models are individualistic, research can and should extract generalities from these scenarios. For example, analysts can measure whether the correlation of states in the model mirrors their correlation in the real world, for the purpose of validation. Generalization is most fundamentally an issue of data representation, and finding the right level of generalization in an ontology that best establishes a correlation is a data processing issue.

TRAC used SIMmiddleware to study the validity of models of its 2010 tactical wargame by comparing model output to Afghan Nationwide Quarterly Assessment Review (ANQAR) data from the same year portrayed in the tactical wargame. Analysts calculated a probabilistic distance between the model and the real-world data using the Kullback-Leibler convergence probabilistic distance function. This equation represents the information lost when one Markov process is substituted for another; specifically, the number of bits needed to make the output of one match the other. The Markov process shown in Figure 3 illustrates results of the validity research from tactical wargame 2010. Nodes indicate types of player actions and the popularity of a coalition player. Arcs represent the likelihood of transitioning between node states. Green areas represent 'good' states (popular) while red areas represent 'bad' states (unpopular). The probabilistic distance between the model and the real-world data shows a score of 0.21, a relatively low probabilistic distance (lower is better). This score served as evidence for the validation of the tactical wargame model at a rudimentary level. Since SIMmiddleware and its implemented probabilistic ontologies preserved the uncertainties in the data, models, and translations between

models, the Markov process represents the best estimate of the probabilities of arriving at different states of interest (Duong & Bladon, 2012).



- **Apply Kullback-Leibler (KL) divergence to measure probabilistic distance between Markov processes:** $D_{\mathrm{KL}}(P\|Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}.$

- **Score of 0 means exact same Markov process. Score of 1 means the most different Markov process possible. Example above generated KL score = 0.21.**

Figure 3. Comparison of Markov processes for validation score.

The concepts of a social theory should enable output data from IW models to correspond to real-world data. The validation analysis from Figure 3 compared model and real-world data regarding simple concepts such as popularity and kinetic actions. However, IW concepts are much more complex, and models representing IW concepts must be formalized to determine whether they align with theory.

The U.S. Army Engineer Research and Development Center's (ERDC) Cultural Reasoning and Analysis for the Tactical Environment (CREATE) offers a good example of such a formalization that could be used to objectively score how closely a simulation conforms to theory (Whalley, Perkins, Krooks, Hargrave, & Rewerts, 2012). CREATE is unique in its formalization of the arguments from social literature that frame the situation in a host country. CREATE's factor map formalizes the social literature on CMO with an augmented version of Shum's Naturalistic Argumentation upper ontology (Shum, Uren, Li, Sereno, & Mancini, 2007). Shum's ontology consists of relations between entities that indicate the degree to which social literature claims support or refute one another. The social literature is annotated with these relationships, so that the analyst can easily query scenario data that support the social model/frame/theory. For example, a theory may claim that insurgency is political in nature while another theory may identify poverty as the root cause of insurgency.

Using CREATE's annotation user interface, an analyst can manually mark claims in the text as major claims of the article, and then mark all supporting claims with links labeled "is evidence for," "proves," etc. (see Table 1). The claims and the link between them form an rdf triplet for a Web Ontology Language (OWL) ontology. The links are weighted to show the level of support (or refutation) one claim has for another. These claims are then linked to claims in other articles as well, to include link labels such as "is inconsistent with." The claims may represent any level of generality, from generalizations about insurgency to specific facts about the insurgency in Kenya. Use of CREATE results in a summarized understanding of the situation in terms of the processes that belong to a frame (for example, whether the insurgency in Kenya is caused by poverty, and if so, the effectiveness of the intended CMO interventions).

Table 1. *Shum's Naturalistic Argumentation Upper Ontology*

Relation Class	Dialect label	Polarity/ Weight
General	is about	+/1
	uses/applies/is enabled by	+/1
	improves on	+/2
	impairs	– /2
	other link	+/1
Problem Related	addresses	+/1
	solves	+/2
Supports/ Challenges	proves	+/2
	refutes	–/2
	is evidence for	+/1
	is evidence against	–/1
	agrees with	+/1
	disagrees with	–/1
	is consistent with	+/1
	is inconsistent with	–/1
Causal	predicts	+/1
	envisages	+/1
	causes	+/2
	is capable of causing	+/1
	is prerequisite for	+/1
	prevents	–/2
	is unlikely to affect	–/1
Similarity	is identical to	+/2
	is similar to	+/1
	is different to	–/1
	is the opposite of	–/2
	shares issues with	+/1
	has nothing to do with	–/1
	is analogous to	+/1
	is not analogous to	–/1
Taxonomic	part of	+/1
	example of	+/1
	subclass of	+/1
	not part of	–/1
	not example of	–/1
	not subclass of	–/1

Note: Table adapted with permission from Shum, Uren, Li, Sereno, & Mancini (2007)

Applying this method to an example from the *Battle of Algiers* scenario, we might find that a news article states that many of the insurgents are well educated. That would conflict with the social theory that poverty leads to insurgency, stated in another theoretical journal article. In this case, the triplet for the news article may be <Ahmed, education level, PhD> and the journal article triplet <Insurgents, economic class, poverty>. The Shum ontology triplet would be <<Ahmed, education level, PhD>, is evidence against,<Insurgents, economic class, poverty>>. When this connection is found, the social theory that poverty leads to insurgency would receive a "–1'. Even an analyst who lacks a formal background in the social sciences can rapidly assess the arguments and evidence that explain the social situation and comprehend the advantages and disadvantages of varying perspectives.

Formalizing the claims of social science and applying them to particular scenarios of IW aids in model validation. The numerical degree of refutation or support of a theory encoded in the Shum ontology links can form an objective measure of how much the model output matches particular social theories. Methods that enable objective measurement of models significantly advance sociocultural model validation requirements.

Although the CREATE methodology was designed for analysts rather than computer models, its formalization of the ideas of sensemaking can model the insights that MISO makes regarding the host population, which in turn are instantiated in CMO interventions. The usefulness of CREATE for modeling CMO resides in its potential for modeling effects of a MISO argument on a host nation population and to counter a terrorist narrative. A major gap in the ability to model the effect of CMO on the host population is the ability to model MISO. Doctrine states that CMO is the evidence of MISO, and that the purpose of CMO is ultimately to influence popular support. However, almost all models of popular support are based on message dissemination dynamics by affinity rather than on the content of the message itself and why that message would resonate with the people.

To model MISO, we must therefore model why a MISO message will resonate with the population and how CMO supports the message. In terms of natural argumentation, the host nation population would have several ways of framing the situation: in terms of their cultural narratives, the CMO actions and the MISO that depicts them, and past perspectives. Insurgents would give evidence that supports some of the population's frames and refutes others. Introducing message content into the modeling of MISO would be a vast improvement over existing algorithms.

8. Model Process Control

Model process control (MPC) uses feedback between data and models to improve both the interpretation of the data and the accuracy of the model. We have described methodologies to extract data, input and execute data in models, and compare model output to real-world data. One data processing methodology for COA analysis involves putting all of these activities together into a feedback loop that interprets data and refocuses models on more salient data. A feedback loop benefits all stages of data fusion because even such fundamental steps as the parsing of free text data depend on meaning. For example, the difference in the parse of the statement "Jack ate the salad with chopsticks" and the statement "Jack ate the salad with croutons" results entirely from

the meanings of words. Applied to the *Battle of Algiers* scenario, a text may mention a man named Ahmed who bought fertilizer—a substance that may be used to nourish crops or to make bombs. The first interpretation would be the triplet <Ahmed, purchase, bomb-materials> and the second <Ahmed, purchase, farming-materials>. A model might retain both interpretations until one or the other approaches certainty. A model can help analysts determine how the interpretation fits in with everything else known about Ahmed. For example, the model could posit that Ahmed was buying bomb materials, but through a motivation-based simulation might determine that at this point in time the insurgent group is highly unlikely to find bombing acts to their advantage (e.g., if the French populace were leaning toward pulling out of Algeria, a bomb attack would be interpreted as a reason to stay in the country). The MPC might then accept the interpretation that Ahmed was a farmer, and refocus its data collection on plans for strikes, which would better achieve the goals of the insurgency at the present stage in the game.

The U.S. Army Intelligence and Information Warfare Directorate (I2WD) is pursuing an MPC project for the Intelligence Community that implements automated feedback loop concepts. Through its Soft Target Exploitation and Fusion (STEF) program, I2WD has previously sponsored projects that can serve as part of the feedback loop. For example, Indra, an NLP program, can enable real-time, evolving data to conform to a model's requirements. Indra generates ontological categories of social roles and role relations that emerge from text and translates them into the particular ontology of a computer model (Duong, Stone, Goertzel, & Venuto, 2010).

One aspect often neglected in sociocultural modeling is the capacity of the model to absorb data. Nexus can serve in another part of a feedback loop by helping a model conform to the data. Nexus uses coevolutionary pressure to explain the statistical patterns in the data through the motivation of the agents, so that the simulation can recreate the same vicious and virtuous cycles that created the data in the real world. This allows interventions to be tested on a natural, self-reinforcing system (Duong, Pearman, & Bladon, 2013).

The capacity to absorb data in simulations is important to federations of models because it enables participants to assume new consensus states. Data processing for COA analysis should account for conflict resolution not only in the data fed to simulations, but also in federated models that overlap. Models that overlap in function can resolve conflicting results using voting techniques to achieve consensus.

Another technique for arriving at consensus related to competing or overlapping functions involves the use of Nexus's neural network for constraint satisfaction. The neural network can place positive links between event relations that are positively correlated in the real world, or that CREATE determines to be consonant with theory. Conversely, the neural network can place negative links between events that are negatively correlated in the real world, or that CREATE determines to be dissonant with theory. Nexus could execute the network to determine simulation outputs that fit best both theory and the real world, and enter them back into all federated models as the consensus state. In this way, the computations that federated models make in an MPC system could include a validation step. The MPC would retain the most valid simulation states that are both consistent with each other and consistent with theory.

9. Science and Technology Gaps in Data Processing for COA Analysis

Industry, government, and academia have all recently made important contributions to data processing for COA analysis in the areas of both model integration and formalization of COA concepts in data. In industry, Impact Computing's XBM integrates models to represent interactions among strategizing minds in general, while Sentia's Senturion integrates a specific cognitive model for political COAs. In government, OSD has researched coevolutionary integration of learning mental models in Nexus, and TRAC has preserved uncertainty in data and translation for risk-based analysis and validation using SIMmiddleware. Additionally, ERDC has formalized evidence and sensemaking data in CREATE, and I2WD is advancing the science of MPC to integrate models in a feedback loop. The Naval Postgraduate School's Simulation, Experiments and Efficient Design (SEED) Center has advanced the science of data farming. In academia, researchers at the University of Arizona, Arizona State University, and Pennsylvania State University have improved the representation of COA extraction from text, narrative extraction from text, and a coevolutionary framework for terrorist learning, respectively. The Department of Defense (DoD) has supported many of these advances. However, gaps remain in the underpinnings of how to use all of these ideas together in a scientifically valid analysis.

Although the tools mentioned in this chapter offer a promising start, they have not solved the problem of valid scientific analysis of social phenomena. These tools begin to deal with the most important data processing gaps for COA analysis—automation, uncertainty, and risk-based analysis—but do not yet form a complete program that has the blessing of the scientific community as the best direction to take, and that can be translated into formulas for use for operational personnel.

In the past, models of conventional warfare only needed a limited amount of pre-validated, physics-based data. In contrast, the IW models of today demand far more data because they are based on the scenario-specific data of social processes. Little scientific research has focused on automating the use of "big data" from the internet. For researchers to use the data live or with any scalability, automated tools must automatically put these data into the ontology needed by the model. Further, models should be modified to accept data that they do not anticipate. Because social science is scenario specific, the social model should not predetermine all of the processes simulated; instead, the data should determine the specific processes while the model only holds general forms of social processes as true. The capacity to automatically absorb data for models goes hand-in-hand with the capacity to automatically represent data for model consumption. Once tools can automatically place the big data of the internet in the correct ontology and resolve conflicts within the data, the data base can become more reliable than the individual data that comprise it. The data can then serve as both a training set for model creation and a testing set for validation.

Uncertainty is another important data processing gap for COA analysis. Non-validated data can potentially conflict. Closing the technological gap by taking advantage of the amount of data for the resolution of conflict in the data, perhaps in a type of automated crowd sourcing technique or other voting system, will permit disparate, conflicting data to form a coherent picture.

Conflict occurs not only in data that go into models but also in data produced by federated models. Overlap in model functionality has benefits because the models can clarify and vote on conflicting areas. Such overlap enables users to test CONOPS for robustness against every plausible model of every school of thought. Data processing techniques of integration, such as voting systems, switching in and out in proportion to pedigreed credibility, or constraint satisfaction systems can handle functional overlap and conflict resolution in models.

Furthermore, risk-based analyses should measure uncertainty and conflict in the data coming into the models and going out of the models. To build scientifically valid models for COA analysis, we must advance the science of data processing to make data available for validation. We also need feedback from data to identify the most promising new scientifically based model technologies. The confidence that analysts have in the data, in the translation of the data, and in the output data should be kept in proportion so that the end result of the analysis retains a probability. The parameters of multiple model runs should be chosen according to their likelihood given other parameters, so that they are realistically correlated. The DoD as a whole would likely have benefited from additional investment in the science of valid social analysis, whether focused on models or on data.

10. Technology Transfer of Data Processing Techniques for COA Analysis

Today knowledge gaps exist regarding processes for integrating new technologies from government, industry, and academia into operational use. This gap in knowledge of the science of IW analysis hinders operators from selecting sociocultural products that could support scientifically valid analysis. Operators need not only the products, but also guidelines for carrying out COA analysis that rest on both scientific theory and the big data of the internet, and that are comprehensible to non-scientists.

Control of operational analysis that uses sociocultural modeling should remain in the hands of scientists until the scientific community comes to a consensus on the direction that scientific modeling of social phenomena should take. The DoD should not prematurely choose a particular direction or constrain the science through standardized procedures of analysis before the natural process of scientific argumentation, experimentation, and validity has reached a consensus from which to draw a procedure. The DoD should not spend 6.4 (demonstation and validation) funds until 6.1-funded (basic research) products are mature, no matter how frustrating the wait. Scientific competition in argumentation and experiment should ideally enable the best ideas to bubble to the top. Short of that, the DoD should hire scientists to spot the best new ideas, rather than having operational personnel under resource constraints control social model analysis.

Once scientists have established and advocated scientifically sound criteria for usage of individual methods, and schools of thought have explored competing paths toward scientific analysis, the scientists can lay out entire maps of the procedures that operations personnel should perform as part of scientifically valid analysis. Without careful review by the best scientists of the day, operational analysis of social phenomena will fail to meet the stringent criteria for scientific validity.

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14 Methods and tools to analyze responding to, counteracting, and utilizing sociocultural behaviors[1]

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1. Introduction

The preceding chapters have explored the complexities of understanding, detecting, and forecasting sociocultural phenomena related to crucial national and international security issues. They showed how human behavior—both individual and societal—represents a confluence of cultural, political, social, economic, and historical factors interacting in a dynamic system. This chapter focuses on leveraging that information to develop effective *mitigation* policies that can respond to, counteract, or utilize these sociocultural behaviors.

In this chapter, we describe some methods and tools for mitigation analysis through computational modeling. We examine several computational approaches to course of action (COA) development, analysis, and comparison, noting the potential for positive impact on the military decision-making process (MDMP), as well as the existing technological gaps that must be filled to achieve effective sociocultural mitigation. This chapter expands on previous discussions of mitigation technologies presented in Kott and Citrenbaum (2009), which focused on the sociocultural factors and the impact on military operations. The particular applications presented here do not represent an exhaustive list of available technology solutions, but rather a sampling of computational approaches that may facilitate military decision making.

The data themselves are central to the problem of mitigation. In the modern information environment, decision makers must contend with an overwhelming quantity of data—ranging from field reports and sensor readings to communication signals and satellite imagery—which, as earlier chapters showed, may potentially contain indicators of extraordinarily intricate sociocultural phenomena. Even with the visualization, data processing, and modeling techniques already described, the amount and complexity of the information to be weighed would overwhelm any human analyst, no matter how talented or knowledgeable. In this chapter, we discuss how computational modeling can relieve some of this burden, allowing decision makers to synthesize and integrate the models, knowledge, and insights from the understand, detect, and forecast phases of analysis to provide better operational awareness. Using many methods similar to the big-data analytics employed by corporations such as Amazon or Google, analysts can exploit this wealth of sociocultural knowledge to support decision making and determine the most robust COA

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in many critical situations. Of course, the vast domain knowledge and experience of military and civilian experts should not be ignored; the computational models described here are intended to augment—not automate—the decision-making process.

In Field Manual 101-5 (U.S. Army, 1997), the Department of the Army specifies a seven-step MDMP: (1) Receipt of mission, (2) Mission analysis, (3) COA development, (4) COA analysis, (5) COA comparison, (6) COA approval, and (7) Orders production. Figure 1 outlines these steps, illustrating both the commander's and the staff's roles in reaching a decision. As noted in Field Manual 101-5, decision making requires an understanding of the possible consequences of a COA and how that COA can contribute to progress from the current situation toward the stated mission goal. The MDMP is designed to facilitate comparison of multiple COAs and analyze them in light of possible enemy COAs or decisions, preventing decision makers from overlooking possible actions, outcomes, or critical aspects of the environment.

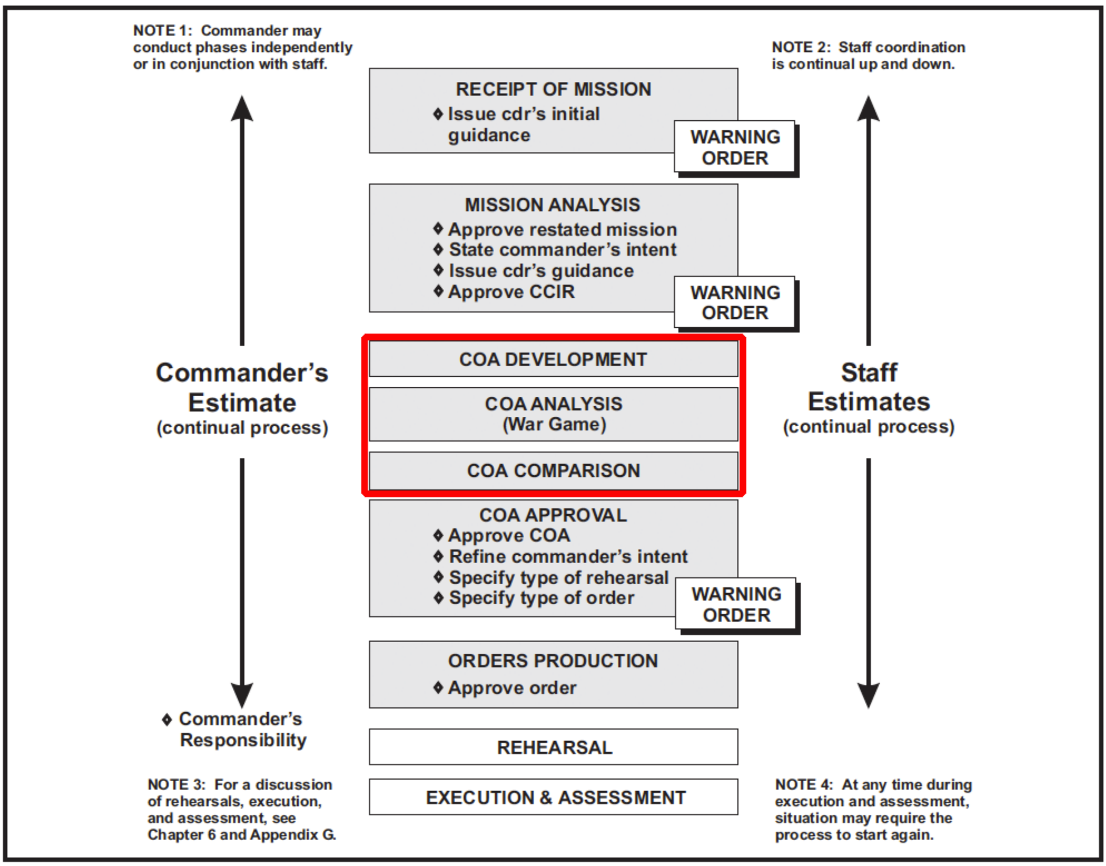

Figure 1. Military Decision-Making Process (MDMP). Adapted with permission from U.S. Army Field Manual 10-5 (1997).

Computational models can expand a commander's ability to examine possible options and account for complex behavioral dynamics when considering COAs and their short- and long-range impact.

Such models have the potential to augment this decision-making and mitigation process at several steps, outlined in red in Figure 1: COA development, COA analysis, and COA comparison.

COA development consists of producing possible COAs for further analysis and comparison (U.S. Army, 1997). All of the COAs must meet some minimal standards of suitability (i.e., adhere to constraints identified by the commander), feasibility, acceptability (in terms of the potential cost-benefit ratio), distinguishability (i.e., contains characteristics that set it apart from other COAs), and completeness. Exploratory computational modeling utilizing the behavioral models and forecasts previously developed for situation awareness can help analysts or decision makers identify COA variants that may yield better outcomes given the sociocultural dynamics of the current context. Below we describe several computational approaches to COA generation, such as abductive reasoning and artificial intelligence (AI) planning.

Typically, COA analysis involves wargaming to identify the strengths and weaknesses of a COA and major decision points that call for additional detail to account for specific situational conditions (U.S. Army, 1997). COA comparison takes this process a step further, presenting detailed analysis of which COAs are effective in particular contexts, and identifying robust options that have a high probability of success in light of the opponent's most likely (or most dangerous) behaviors (U.S. Army, 1997). Computational models capable of utilizing complex knowledge of sociocultural phenomena can facilitate both of these aspects of the MDMP. Approaches such as social network analysis and tools such as dynamic systems models and multi-agent simulations can compare the potential outcomes of various COAs (both human and model generated) under a wide range of plausible conditions to support the MDMP.

2. Mitigating Violent Behavior in Pakistan

Analysis of the sociocultural and behavioral landscape, including factors such as potential reactions of adversaries and possible roadblocks resulting from civilian cultural perspectives, is essential to the success of the MDMP. Computational models can support the MDMP by allowing officers and staff to exploit large quantities of sociocultural data and expanding their capabilities for COA analysis and comparison.

As an example, we present a complex counterterrorism scenario where a decision-making team must develop policies to mitigate the destabilizing violence perpetrated by the terror organization Lashkar-e-Taiba (LeT) in Kashmir and India. LeT has a sophisticated leadership structure and an active militant wing capable of executing complex, coordinated attacks throughout the Indian subcontinent and the world. While the organization may originally have sought only the liberation of Kashmir and establishment of an Islamist Pakistan, since the attacks on September 11th, 2001, LeT has contributed recruitment, training, personnel, and funding to the global jihadist movement. The group plays a complicated role in the sociocultural dynamics in Pakistan, using terrorist tactics to wage jihad in India, Afghanistan, and around the world, while being deeply integrated into the local social fabric through its charitable activities and provision of services that the government cannot maintain.

What counterterrorism policies might be most effective in discouraging LeT's use of violence? How can we disrupt or counter LeT propaganda conveyed via their widespread communications, education, and social services networks without threatening the security of the Pakistani citizens who rely on these services? How can the decision makers leverage their knowledge about the cultural and behavioral dynamics of LeT and the Pakistani people to achieve broader goals of security and stability within Pakistan and the region? Finding answers to these questions will require analysis of a multifaceted sociocultural landscape, augmenting human judgment and expertise with large-scale computational modeling and simulation.

3. Goal-oriented Automated COA Development

Given a particular mission and models for understanding, detecting, and forecasting sociocultural factors within the operational context, the first phase of military decision making involves developing possible COAs that could feasibly achieve the mission goals. Researchers in the field of AI have applied two main approaches to developing COAs through this type of *goal-oriented* reasoning: logical abduction and AI planning. They have used these methods, along with the predictive models discussed in Chapter 10, to construct large-scale decision support software systems used in several public and private sector decision-making processes. The computational models can generate possible mitigation policies, assess their probability of effectiveness and acceptability relative to resource and feasibility constraints, and elucidate the factors that contribute to better versus worse outcomes. Below we briefly describe the two approaches, providing some examples of possible applications and specific tools that can contribute effectively to mitigation.

3.1. Abductive Reasoning

In many everyday situations, people must interpret a set of observations, using their past knowledge of how the world works to explain the current situation. For example, a homeowner wakes up in the morning and notices that her lawn is wet. From prior experience, she knows that if it rains during the night, then her lawn will be wet in the morning. Therefore, she can conclude that it probably rained during the past night, and she may decide to carry an umbrella to work in case the bad weather continues. That, in essence, is the process of educated guessing that all people employ countless times per day: given some behavioral rule, people can form hypotheses and draw conclusions about entirely new situations. This type of reasoning is known as *abduction* (not to be confused with kidnapping!) Abductive reasoning centers on finding the most logical and relevant explanation for a set of facts. This mode of thinking is used extensively in intelligence analysis and complex decision making.

This type of reasoning does not limit people to explaining observed facts; they can use the same process to develop possible COAs instead of hypotheses (e.g., taking an umbrella to work). Basically, using abduction for COA generation involves selecting the "optimal" subset of *actions* that, when executed in the current situation, will achieve the stated goal with the highest probability, taking some possible constraints into account. The definition of optimality depends on many factors, such as the current operational environment or limitations on time or resources.

Constraints may correspond to choosing the shortest COA (either in terms of the number of distinct steps or the total time to execute the plan), the least expensive COA, etc.

The Policy Analytics Generation Engine (PAGE) develops possible COAs using both exact and approximate abductive computations, while the APT (Annotated Probabilistic Temporal) Abduction System (Simari & Subrahmanian, 2010; Molinaro, Sliva, & Subrahmanian, 2011) centers on more complex temporal aspects of COA generation. The Spatio-Cultural Abductive Reasoning Engine (SCARE) system successfully uses abduction to identify the location of weapons caches and improvised explosive devices (IEDs) in combat zones, allowing for development of specific mitigating COAs (Shakarian, Subrahmanian, & Sapino, 2009; Shakarian, Subrahmanian, & Sapino, 2011; Shakarian, Nagel, Schuetzle, & Subrahmanian, 2011). In these systems, rather than start from a set of facts or observations, users set a goal—e.g., reduce LeT use of bombings by 50%—and find an "explanation" that will enable progress from the current situation toward this goal.

If the strategic goal is to disrupt LeT's use of *fedayeen* attacks (suicide attacks) in Kashmir, the decision maker's objective is to identify ways of reducing these attacks, rather than explain how or why LeT engages in such attacks. The PAGE system utilizes contextual data about experience with combat in the region and sociocultural data regarding LeT's behavioral dynamics to determine the best way to prevent *fedayeen* attacks. The software outputs a set of actions that, when executed, would change the current situation to one in which *fedayeen* attacks have been reduced. To create deeper insight into how such COAs should be implemented, the APT Abduction System adds temporal analysis, providing the optimal time frame within which each component of the COA should be executed. This style of abductive reasoning assists analysts as they look for a strategy that can induce the desired effect, rather than perform data analysis to describe the strategy after the fact.

Abductive reasoning can also be used for more tactical-level reasoning, such as identifying and destroying enemy weapons caches in a combat zone. Rather than explain the opponent's attack strategy, the SCARE system utilizes event data and spatial sociocultural information from real combat (for example, some groups tend to place weapons caches in close proximity to IED attack sites) to indicate likely locations that should be targeted for raids or further investigation. An extension to this system is in development for locating other types of high-value targets in a counterinsurgency environment, particularly Afghanistan.

The main distinction among the abductive reasoning frameworks above results from the underlying data needed to use the systems. PAGE requires behavioral data: what events have occurred, how the group in question has responded to past strategies, etc. APT Abduction requires time-annotated behavioral data, covering not only what decisions the group has made, but also the time lags between changes in their environment, observed behaviors, and possible outcomes. SCARE relies on spatial sociocultural information: the coordinates of past attacks, the movement patterns of the group, etc. The choice of system depends on the available data and the problem a commander needs to solve. For example, if intelligence indicates that LeT will attack in India in one week, analysts might direct APT Abduction to generate all COAs that can be completed in under a week.

Event tracking, mobile phone records, satellite imagery, and the various models and data processing tools described in Chapters 1, 5, and 9 of this book can supply much of the necessary data. However, a key step in abductive reasoning and COA development relies on appropriate processing of the raw data to make them usable by the models and reasoning systems. PAGE, APT Abduction, and SCARE all rely on a data representation method known as probabilistic logic (Molinaro, Sliva, & Subrahmanian, 2011; Simari, Dickerson, Sliva, & Subrahmanian, 2012). Probabilistic (and temporal) logic has been extensively studied and used in several applications as a stochastic representation of the behavioral dynamics in international security situations, such as terrorism, drug trafficking, and ethno-political violence. Fagin, Halpern, and Megiddo (1990), Hailperin (1984), Lukasiewicz (1998), Ng and Subrahmanian (1992), and Nilsson (1986) give technical details of probabilistic logics; Mannes, Sliva, Subrahmanian, and Wilkenfeld (2008), Mannes, Michael, Pate, Sliva, Subrahmanian, and Wilkenfeld (2008), Sliva, Martinez, Simari, and Subrahmanian (2007), and Subrahmanian et al. (2007) describe sociocultural modeling applications of probabilistic logics. The benefit of this probabilistic logic-based approach results from the balance between formal reasoning—mathematical models that computers can easily manipulate—and expressive power that human users can understand.

Probabilistic logic explicitly ties behavioral and cultural dynamics to facts about the world environment, relating the probability of actions to potential contextual factors, such as the political conditions (e.g., existence of repressive government policies, occurrence of elections, corruption, etc.), sociocultural factors (e.g., religious beliefs, ethnic cleavages, leadership structures, etc.), or economic conditions (e.g., business relationships, economic grievances, macro-economic indicators, etc.). Such rules can be extracted from the behavioral or spatial data previously mentioned (Khuller, Martinez, Nau, Simari, Sliva, & Subrahmanian, 2007). Figure 2 contains a sample of a probabilistic logic representation of some behaviors of a terror organization like LeT, indicating the probability of violent actions as a result of situational factors in the environment (Subrahmanian, Mannes, Sliva, Shakarian, & Dickerson, 2012). The first line says that if the group is experiencing conflict with another rival organization (i.e., interorganizational conflict), then the probability that it will use kidnapping as a strategy lies between 0.35 and 0.45.

Probabilistic Logic Model of Terrorist Behavior

1. $\text{kidnap} : [0.35, 0.45] \leftarrow \text{interOrganizationConflicts}.$
2. $\text{kidnap} : [0.60, 0.68] \leftarrow \text{unDemocratic} \ \& \ \text{internalConflicts}.$
3. $\text{armed\_attacks} : [0.42, 0.53] \leftarrow \text{typeLeadership(strongSingle)} \ \& \ \text{orgPopularity(moderate)}.$

Figure 2. Example of probabilistic logic rules describing the behavior of a terror organization.

Unfortunately, abductive COA generation can be computationally very intensive, making it difficult to incorporate the systems mentioned above into real-time decision making. Researchers have developed a more scalable distributed framework that can approximately solve for the top *k* possible COAs (where *k* is an amount determined by the user) (Simari, Dickerson, Sliva, & Subrahmanian, 2012). This method utilizes parallel computation to process large quantities of sociocultural information simultaneously, generating several different COAs with different starting assumptions. For example, the analyst may look for COAs to fit a hypothetical situation in which Hafez Saeed, the leader of LeT, is under house arrest, or COAs that would prevent him from finding robust solutions to a variety of contingencies. Approximations can allow decision makers to develop many alternative mitigation policies in a more tractable timeframe.

Another flavor of abductive reasoning utilizes Markov logic networks (MLNs) rather than probabilistic logic. MLNs resemble probabilistic logic in that they attempt to combine the expressive power of logic (often necessary for sociocultural models) with the uncertainty computations of probability theory (Kok & Domingos, 2009; Richardson & Domingos, 2006). However, MLNs place even greater emphasis on the relational aspects of the environment, producing a network structure that can leverage algorithms, visualization tools, and human expertise developed for related graphical models such as hidden Markov models, dynamic Bayesian networks, or conditional random fields. MLNs are more suitable than those approaches for sociocultural domains because of their natural representation of complex behavioral data, such as the kind developed using the methods in Chapters 1, 5, and 9.

In MLNs, all of the environmental factors (political conditions, sources of funding, economic situations, etc.) and behaviors (kidnapping, suicide bombing, etc.) that describe a group are nodes in a graph and are connected according to their probabilistic cause and effect relationships (Pearl, 1988; Richardson & Domingos, 2006). Recall the (partial) model from Figure 2 of a terrorist group's violent behavior in the Middle East. Logic rules (1) and (2) reveal two possible relationships between the operational context and the occurrence of kidnapping. In the first case, interorganizational conflict is a potential indicator that kidnapping will occur; in the second case a combination of nondemocratic group leadership and internal conflict within the organization affects the likelihood that it will use kidnapping as a strategy. An MLN can represent these possibilities as shown in Figure 3. Because interorganizational conflict is related to kidnapping, the analyst draws a line connecting these two ideas. Since both non-democratic group leadership and internal conflict relate to kidnapping as well, the analyst connects these with the action; to indicate that these two factors must occur at the same time, the analyst also draws an edge connecting them. This small MLN compactly and visually captures these complex relationships between the environment and observed sociocultural behaviors.

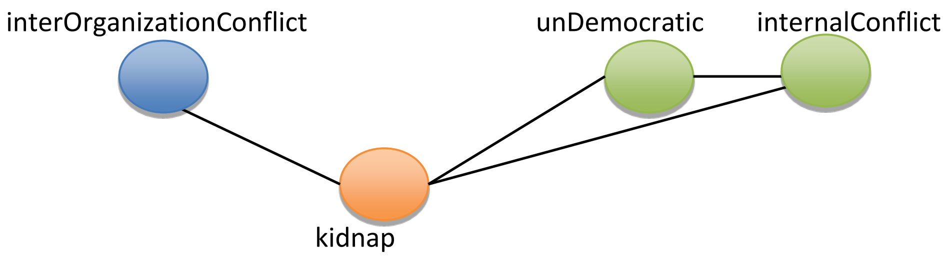

*Figure 3***.** Markov logic network representing factors that contribute to LeT's decision to use kidnapping.

Some recently developed systems can apply these MLNs to probabilistic abduction (Kate & Mooney, 2009; Singla & Mooney, 2011). These processes use the graphical structure to facilitate efficient analysis and identification of possible policies. For example, the MLN in Figure 3 clearly contains two separate sections pertaining to kidnapping. If the goal is to reduce kidnapping, then an analyst can quickly identify the relationships that lead to the lowest likelihood of kidnapping. In this case, rule (1) shows that fostering intergroup conflict might be one aspect of a COA to counter the organization's militant strategies. Because MLNs are easy to visualize, decision makers in the field can use them for real-world COA generation. Both MLNs and probabilistic logic frameworks use the concept of abductive reasoning to develop possible COAs that directly utilize the sociocultural understanding we have developed. These COAs can supplement human-generated COAs and be further compared and analyzed either manually or with additional computational models described in section 4 of this chapter.

3.2. Artificial Intelligence Planning

AI planning also explores computational models for automated COA discovery, and may provide more efficient algorithms or intuitive representations in some tactical domains. Like abduction, AI planning is goal-based, searching for possible COAs that can achieve a mission given the current operational environment and some possible constraints on time or resources.

Particularly relevant to the complex, dynamic situations confronting military decision makers is the need to plan under uncertainty. In this type of AI planning, models generate COAs in a probabilistic domain to capture uncertainty about either the outcomes of actions, the current situation, or both. In many operational environments affected by sociocultural dynamics the outcome of a COA (or part of a COA) may be uncertain—how will an adversary or civilian population react to a particular action?—but, more important, analysts may be uncertain about the exact nature of the human terrain. Their sociocultural understanding will provide information about the possible behaviors that may have an impact on a COA, but the complexity of social processes means that the resulting models may be incomplete, noisy, and uncertain. There may simply be some parts of the operational situation that military units cannot (or do not) monitor. To account for these gaps in knowledge, analysts can use a computational COA discovery model based on partially observable Markov decision processes (POMDPs) (Kaelbling, Littman, & Cassandra, 1998; Kobolov & Kobolov,

2012). POMDPs have been utilized in many real-world applications: Yost and Washburn (2000) developed methods for solving large-scale military allocation problems with POMDP algorithms, and MIT Lincoln Laboratories and the National University of Singapore are exploring a variant of POMDPs as a method for automated collision avoidance in unmanned aerial vehicles (Bai, Hsu, Kochenderfer, & Lee, 2012).

The immense complexity of the problem can make exact algorithms for solving POMDPs and generating possible COAs intractable in real-world cases. Current research in AI planning has developed several heuristic approaches that may make POMDP models more accessible to users who need to incorporate sociocultural knowledge, allowing them to access these decision-making aids in near-real time using the limited computing resources available in the field (Ross, Pineau, Paquet, & Chaib-draa, 2008). Heuristic approaches make trade-offs between accuracy and efficiency, meaning that developers must give careful consideration to the role of human decision makers in ensuring accuracy of these systems.

During COA generation it is often crucial to identify the low-level tasks that must be accomplished to achieve a broader mission goal. This type of planning can utilize an automated planning approach known as hierarchical task networks (HTNs), which explicitly decomposes the COA into smaller subtasks. For example, a decision maker may want to formulate a high-level plan to reduce the number of *fedayeen* attacks in Kashmir by LeT militants. Using an HTN system, the decision maker might decompose this problem according to the hierarchy in Figure 4. Reducing *fedayeen* attacks has two components: ending Pakistani military support of the LeT militants and disrupting the internal cohesion of the organization. The second component consists of two pieces: encouraging the LeT leadership to resign and causing the group to splinter. Of course, both of these subtasks are very broad in and of themselves, and in a real-world HTN planner they would be further divided into lower level operations to accomplish each of these goals.

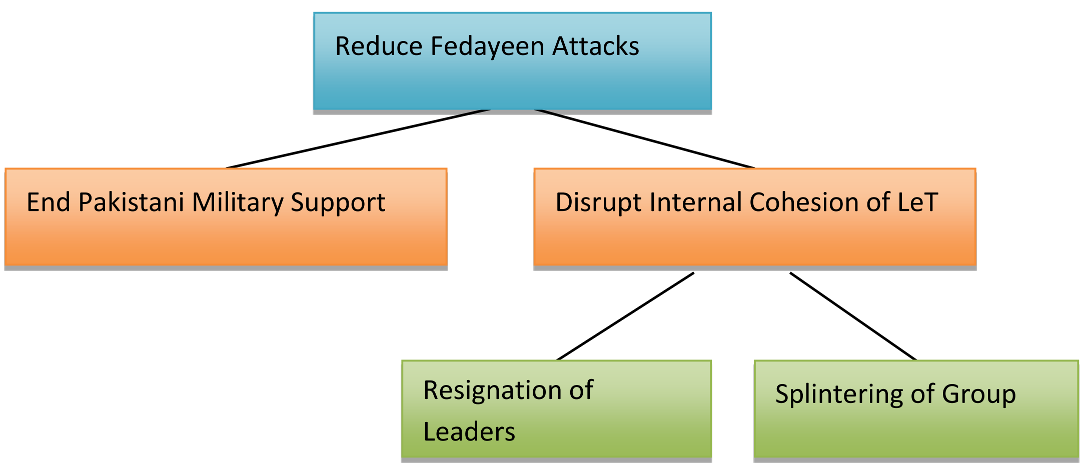

Figure 4. HTN for reducing LeT *fedayeen* attacks. The network decomposes the main goal into component parts, each of which might be further subdivided into several possible COAs.

HTNs can automatically explore different possibilities or combinations of actions to construct possible COA options that address the subtasks in the network. Because they portray the structural relationships among different aspects of a COA, planning focuses only on COAs that consist of actions that help to achieve a subtask. This directed approach leads to computation that can be more efficient for COA generation (Nau, Ilghami, Kuter, Murdock, Wu, & Yaman, 2003).

The SOCAP (System for Operations Crisis Action Planning) HTN framework, created by SRI International and tested in the field, uses a variety of data, such as threat assessments, terrain analysis, force deployment, transport capabilities, enemy behavioral factors, and operational constraints, to find possible plans. SOCAP decomposes a library of military actions into subgoals, allowing the user to select a particular objective (e.g., disrupt LeT communications), define the constraints on the environment (e.g., input the necessary sociocultural, political, geographical, etc., data), and compute possible COAs for tactical situations, such as determining equipment configurations or emergency response. The Army has also investigated HTN planning for use in small unit operations (Bienkowski, des Jardins, & Desimone, 1994; Tate, Levine, Jarvis, & Dalton, 2000). In this application SOCAP automatically translates the OPORDs (Operations Orders) produced by high levels of the military into an HTN. Users can then choose from a menu of possible objectives and use the system to generate plans for various tactical environments, such as a counterinsurgency scenario. However, few of the most recent advances in AI planning have so far been incorporated into deployed systems.

Another subset of AI planning particularly relevant to COA discovery in a complex sociocultural domain is the field of *mixed-initiative planning and scheduling* (MIPAS) (Bernstein, Beranek, Inc, & Mcdermott, 1996). MIPAS combines the efficiency and data processing capabilities of automated planners with the specialized human-in-the-loop knowledge of expert users. Where POMDP or HTN planners depend on complicated probabilistic algorithms that can be incomprehensible to actual users, decision makers may find MIPAS approaches more intuitive; rather than wait for the result of a systematic search, the user directs COA generation by dynamically indicating to the system those factors that are most relevant and must be explored or by choosing partial COAs that are most useful. As the situation on the ground changes, the user can simply click the appropriate options on the system to indicate a change in preferences. Several MIPAS planners have been developed for specific applications, such as activity plans for the Mars Rover (Bresina, Jonsson, Morris, & Rajan, 2005) and an interactive COA planning system based on the Air Force Research Laboratory's Causal Analysis Tool (CAT) (Kutur, Nau, Gossink, & Lemmur, 2004). This system allows users to iteratively create plans using CAT's causal networks for analysis and comparison. In addition, research into general MIPAS frameworks, such as the Goal Transformations (GTrans) Planner, can potentially be adapted to COA generation by using available sociocultural data as input and domain experts as the interactive users (Cox, 2003; Zhang, Cox, & Immaneni, 2002). GTrans has already been applied to emergency response situations (Immaneni & Cox, 2004).

All of the above methods can aid decision makers in identifying possible COAs in a particular operational environment. Computational decision support systems (DSSs) can enable decision makers to tap the vast sociocultural information from the understanding, detection, and forecasting phases that may be too complex for experts to analyze manually. In addition, because

such computational methods are not subject to the same cognitive biases or stressful situations as human experts, these systems make it possible to automatically generate COAs that might otherwise have been overlooked.

4. Dynamic Simulations for COA Comparison and Analysis

Once analysts have developed several candidate COAs, either human or automatically generated, the next phases of the MDMP involve comparing the possible COAs and analyzing their relative strengths, weaknesses, and likelihoods of success. Computational models can facilitate comparing and analyzing COAs, allowing decision makers to consider a much broader range of possible social dynamics that could influence COA effectiveness. Computational modeling, such as dynamic simulation systems, can help identify the most robust COA, the one that will best balance resources and feasible success in a complicated sociocultural context (Bankes, 2002; 2010). The following subsections detail several of these methods, focusing on the ways that models developed for sociocultural understanding, detecting, or forecasting can be repurposed and combined for comprehensive COA analysis and comparison.

Dynamic simulation systems harness computational power to determine the most probable outcome of a COA, using the behavior of the model to analyze complex sociocultural factors and interactions that may have an impact on COA success. These simulations effectively comprise a virtual laboratory where analysts can capture the full decision-making processes of adversaries or societies of interest and evaluate how effectively a COA can mitigate such behaviors. By examining how behaviors evolve over time, they can capture emergent or adaptive behavior that may influence seemingly robust COAs. For example, a COA intended to induce internal conflict within LeT may achieve this ultimate outcome, but during the course of its application lead to increased instability in northern Pakistan. Thus, choosing the most robust COA does not depend only on the end result, but also on the intermediate effects.

4.1. Game-theoretic and Cognitive Simulation Models

Chapter 2 in this book presented several variations on rational choice and game-theoretic models. Such models can also be used to analyze possible mitigation options, allowing decision makers to explore the effects of particular actions on the decisions and behaviors of adversaries or societies (Myerson, 1991; Raiffa, 2002; Sandler & Arce, 2003). The main organizing principle for these models is rational choice theory, whereby actors make decisions to maximize potential benefits and minimize costs based on their preferences and the expected actions of other actors.

Recent work on dynamic game-theoretic models incorporates *bounded rationality*, relaxing the concept of rational behavior and including elements from cognitive or behavioral psychology (Cramerer, 2003; Gigerenzer & Selton, 2002). Simulation analyses can use such game-theoretic models in comparing the adversary behavior that will occur as a result of various potential COAs. For example, a system developed by scientists at the Duke University Institute for Homeland Security Solutions combines the adversarial aspects of game theory with the uncertainty and psychology of risk analysis, recognizing that behavior may change in probabilistic ways depending

on conditions of risk (Banks, 2009). Using Bayesian statistics, the system induces a probability distribution over a possible set of outcomes at each time in the simulation, describing the possible costs/benefits of a given COA relative to a particular enemy strategy.

In a dynamic simulation, users can initialize the model with data from the current operational environment and use the probability distribution to examine all possible combinations of friendly and opponent COAs at each time point. This gives the system enough information to compute a cost-benefit analysis for each possible COA under consideration, comparing the relative probability of success in light of the most likely adversary behavior (Banks, 2009). Repeating this simulation multiple times can generate further support for a decision, enabling comparison of COAs based on the number of times the system chose each one as the optimal solution. The more frequently a COA is chosen, the more robust it may be as a mitigating policy. This risk-based framework has been used in real-world bioterrorism scenarios to analyze possible defensive COAs (Banks & Anderson, 2006).

A similar simulation approach explicitly incorporates the psychological dynamics of threat perception into game-theoretic simulations. Behavioral psychology and political science have noted the impact of threat on decision making (Huddy, Feldman, Taber, & Lahav, 2005; Pyszczynski, Solomon, & Greenberg, 2003; Schelling, 1960), where actors suddenly and drastically change their preferences under fear or stress (Kahneman & Renshon, 2006; Kahneman, Slovic, & Tversky, 1982). Researchers at Northeastern University have developed a game-theoretic simulation model based on decision making under threat (Kohentab, Pierce, & Ben-Perat, 2012; Pierce, Boulay, & Malioutov, 2011; Pierce, Boulay, & Malioutov, 2012). At every time point in the simulation, the model computes the threat perception for each friendly and enemy group based on events in the previous time; for example, if an attack occurred in that period, threat perception may have increased. The model incorporates these psychological responses to conflict events into a game-theoretic framework by determining each actor's preferences at each time point. This framework enables analysis of the efficacy of various COAs by noting the level of threat they induce throughout the simulation and the persistence or desistance of violent strategies over time.

While these approaches can enable analysis of how each possible COA will interact with an adversary's cultural and behavioral processes, it is not always possible to model truly emergent or adaptive social behavior with game-theoretic approaches because of their strict mathematical representation. The following sections describe multi-agent and complex network simulation models that can analyze COAs in light of dynamic and nonlinear behavioral models.

4.2. Complex Systems and Network Simulation Models

Complex systems science is the study of emergent behaviors within a large, interconnected system. Dynamic network simulation models offer one representation for complex systems approaches. Chapter 2 presented a detailed discussion of social network models and social influence network theory. Decision makers can use many of these same models for COA analysis to identify how reactions, perceptions, or ideas may spread through a population during implementation of a COA.

In addition, several network simulations have been developed specifically for COA analysis, utilizing structural information about sociocultural factors to map the influence of a COA. Pythia, a computational modeling tool developed by researchers at George Mason University, uses a timed influence network model to graphically represent causal relationships in a social process (Wagenhals & Levis, 2007). In this network, root nodes (nodes with no incoming edges) indicate a particular COA, including the time sequence of its component actions, while leaf nodes (nodes with no outgoing edges) represent possible final outcomes. The interior part of the network models the flow of influence and events, where a direct connection indicates a causal link, each with an associated conditional probability distribution. The system allows users to incorporate time lags into the COA events to see how the network will evolve over time.

Figure 5 traces the effects of a COA where (a) LeT's communications are interrupted, (b) LeT camps are disrupted, and (c) the Pakistani military ceases to support the group. This analysis examines the impact of the COA on the internal cohesion of LeT, which in turn has a causal impact on LeT's executing an armed attack. (Of course, in a real model the single node representing LeT internal conflicts could be a large social network representing the social dynamics of the group and its constituents.) As each element of the COA goes into effect according to the time delay, the probabilities of various aspects of LeT's internal conflicts change; this effect propagates to the likelihood of LeT's carrying out an armed attack. The Pythia simulation system makes it possible to map out the likelihood of specific outcomes—such as LeT's use of violence—as a result of social processes that evolve as a COA progresses. This facilitates comparison between various COAs or different temporal variations of the same COA (Pachowicz, Wagenhals, Pham, & Levis, 2007; Pythia: Timed Influence Net Modeler; Wagenhals & Levis, 2007).

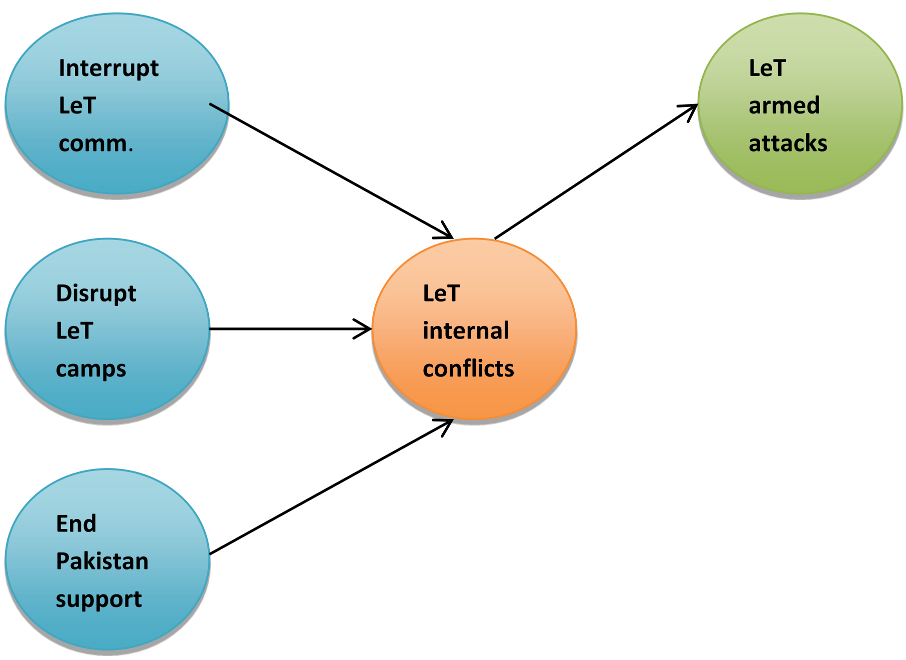

Figure 5. Influence network indicating the impact of a possible COA on the likelihood of LeT internal conflicts and behavior.

The Organization Risk Analyzer (ORA), developed by the Computational Analysis of Social and Organizational Systems lab at Carnegie Mellon University, is another dynamic network analysis and simulation tool that can facilitate COA analysis (Carley & Pfeffer, 2012; Moon, Carley, & Levis, 2008). ORA models the internal social and structural dynamics within an organization or sociocultural group. To use this tool for COA analysis, analysts must link the elements of the COA to relevant parts of a dynamic sociocultural network created for either understanding or forecasting in this domain (see Chapters 2 and 10), similar to the Pythia example in Figure 5. ORA can then analyze the impact of the COA in terms of the vulnerabilities or risks introduced into the network, how the sociocultural system changes over time, and the interaction among various different networks of interest (Carley & Pfeffer, 2012; Carley, Pfeffer, Reminga, Storrick, & Columbus, 2012; Moon, Carley, & Levis, 2008). Depending on the goals of the mission, decision makers can compare these COAs to determine the most robust option.

Basic research advances in complex science make COA analysis for mitigation a promising field for modeling (Barabasi, 2002; Bar-Yam, 2003). For example, several other models have been applied to COA analysis and comparison, such as the New England Complex Systems Institute model for comparing possible intervention policies to stem the production of poppy in Afghanistan, or support counterterrorism efforts and explore how policies with a negative perception may increase instability or volatility (Fostel & Geanakoplos, 2012; Lewling & Sieber, 2007; Widener, Bar-Yam, Gros, Metcalf, & Bar-Yam, 2012).

4.3. Multi-agent Simulations

Chapters 2 and 10 discussed the application of agent-based models to understanding and forecasting behavior in sociocultural systems. These models represent a complex system as a collection of autonomous decision-making agents that can execute behaviors according to specific sociocultural interactions (Bonabeau, 2002). The same modeling and simulation frameworks that facilitate sociocultural understanding or forecasting can also be used for COA analysis, testing the impact of potential COAs in an interactive and interconnected social environment.

One simulation tool under development for agent-based COA analysis is the Course of Action Analysis with Radio Effects Toolbox (CARET), created by RAM Laboratories (McGraw, Shao, Mumme, & Macdonald, 2009). While still in the prototype phase, CARET has provided an agent-based analysis of complex behavior in a military mission context through dynamic COA simulations that facilitate real-time decision making. CARET enables users not only to evaluate the current COA in real time, but also to simulate and compare new possible COAs to determine if a change of course might be more effective. This system is particularly designed to aid in replanning efforts: that is, updating a COA in light of new information or events in the operational environment. For example, during the execution of a policy to disrupt operations at LeT's main training compound near Muridke, Pakistan, the social situation may become unstable due to arrests of LeT members elsewhere in the country. Modelers can collect the new behavioral dynamics of this situation and incorporate them into CARET to further analyze COA viability.

Research by Laval University in Canada has also explored explicit use of Multi-Agent Geosimulation (MAGS) to support qualitative analysis of different COAs (Haddad & Moulin, 2008). This system is designed specifically to facilitate the type of "what if" analysis necessary for comparing the outcomes and side effects of various COAs in a complex sociocultural environment. Analysts can use the implanted MAGS-COA to simulate the execution of a COA in a particular virtual geographic environment that describes the geographic features of the operational theater and can change dynamically along with various sociocultural processes. Users can explore various COAs and assumptions through the agent-based simulations, modeling how the environment evolves over time as the COA is implemented. The MAGS-COA system also directly facilitates COA comparison, producing a qualitative report at the end of the simulation runs that documents the impacts of various potential COAs and their relative success in achieving particular mission goals (Haddad & Moulin, 2008). Similar analyses can also be run using the multi-agent understanding and forecasting simulations described in Chapters 2 and 10.

5. Decision Support Systems

The previous sections have briefly introduced some computational modeling methods with the potential to augment the MDMP, allowing users to leverage large quantities of sociocultural data, models, and forecasts in conjunction with their own specialized knowledge. However, many of the techniques described above are still being explored at the basic research or prototype level. To enter operational use for real-world COA discovery, analysis, and comparison, these computational models must be integrated into comprehensive applications known as DSSs. A DSS is typically defined as an interactive computer-based system intended to help decision makers use communications technologies, data, documents, knowledge and/or models to identify and solve problems, complete decision process tasks, and make decisions (Druzdzel & Flynn, 2002; Shim et al., 2002). Developers have created DSSs since the 1970s for a wide range of domains—medicine, business, air traffic control, military, etc.—that require complex decision making or logistic planning. Recent technological advances have led to a resurgence in DSS research and development, with many promising applications. The military has long utilized DSSs for non-battlefield decisions, such as personnel housing plans in the Army and the U.S. Transportation Command's Regulating and Command & Control Evacuation System (TRAC2ES), developed by Booz Allen Hamilton, for medical evacuation logistics (Booz Allen Hamilton, 2003). Several other DSS frameworks have been developed for military decision making, but have not been widely deployed.

Researchers from the University of Minnesota, the U.S. Air Force Academy, the National Aeronautics and Space Administration, the Department of the Army, and the University of Illinois have developed a suite of decision support tools for various phases of the MDMP, including generation and analysis of COAs and enemy COAs (ECOAs). FOX-GA, an AI planning-based system, uses genetic algorithms to discover COAs for military maneuvering, providing users with a range of possible options in a time-constrained environment (Schlabach, Hayes, & Goldberg, 1998). To complement these COAs, the Weasel system uses a behavioral model of an enemy or other third party to identify possible ECOAs that could result from each possible COA (Larson & Hayes, 2005; Hayes & Ravinder, 2003; Ravinder & Hayes, 2003). Weasel implements a mixed-initiative planning interface and can facilitate a "what if?" style of COA analysis. These two systems are designed to be

used in conjunction with the CoRaven (or perhaps other modeling or forecasting tools) system for intelligence analysis (Jones, et al., 1998). Together, these individual DSSs can constitute a more complete decision support framework for mitigation.

The Massachusetts Institute of Technology (MIT) Lincoln Laboratory is also working on a system for integrated sensing and decision support, with specific research programs in a variety of military applications ranging from special operations to missile defense to air traffic control (Senne & Condon, 2007). This framework integrates remote sensing data, which may include sociocultural sensors such as social media or the outputs of various forecasting or detection models, into a system for decision support, simplifying the decision-making process and incorporating otherwise unavailable information.

Typically, DSSs perform most effectively in augmented decision making, facilitating human decisions rather than fully automating the analysis and final choice of COAs. These tools can help speed up the MDMP at crucial points or permit a deeper understanding of the operational environment, particularly in cases where complex sociocultural factors must be taken into consideration. This is especially true in the sociocultural domain, where even large-scale models still contain high levels of uncertainty (Bankes, Popper, & Lempert, 2006). By providing for a more efficient and complete MDMP, a DSS can help reduce the burden of complex decision making in very high-stakes situations. Of course, decision makers may be tempted to *over-rely* on a DSS; adequate training and continual assessment are necessary to ensure correct utilization of a deployed DSS.

One of the other potential benefits of using a DSS for mitigation stems from the ability of such tools to “de-bias” COA generation or analysis (Davis, Kulick, & Egner, 2005). Unaffected by the preconceptions inherent in human decision making, DSSs can promote objective decision making by generating COAs that a particular decision maker would otherwise not have considered or by analyzing possible COAs from an impartial perspective. However, some studies have shown that use of computational decision aids can actually worsen, or at the very least fail to combat, existing cognitive biases (Davis, Kulick, & Egner, 2005). In spite of the potential drawbacks of DSSs, these computational approaches to decision making can provide an excellent resource for sociocultural mitigation, making the MDMP more efficient and allowing a richer analysis of the operational environment.

6. Operational Challenges of Computational Mitigation Models

As with all new technologies, the devil is always in the details. Implementing effective DSSs or other computational models for mitigation in sociocultural environments remains a complicated technological, engineering, and training challenge.

From a research and development perspective, research must still fill many gaps before any of the above mitigation models can be deployed for operational use. Currently the MDMP can be very slow, but commanders are under extreme pressure to quickly find robust and effective COAs in severely time-constrained environments. While the computational models described above allow

users to consider far more data regarding sociocultural dynamics than a human alone could analyze, the high complexity of the data means that these models may not necessarily arrive at a solution faster.

In many cases, these computational models and simulations not only require excessive running time, but also consume massive amounts of computing resources to process the large quantity of data and complexity of the sociocultural dynamics. While high-performance and distributed computing platforms, such as Apache Hadoop (Apache, 2012), are becoming increasingly available off the shelf, they still require substantial computation resources, usually available only in garrison or at the largest deployed facilities. Because DSSs are intended to augment expert decision making, the COA discovery or comparison should not be performed remotely by users who lack first-hand knowledge of the situation on the ground. The true challenge, therefore, is to provide decision support in real time so that decision makers can use these mitigation models in the theater of operations. To enable such use in the field, researchers must develop large-scale systems that do not depend on physical access to high-performance computing systems.

The previous discussion also assumes that large-scale DSSs can be developed from various component sociocultural models and that information from the models for understanding, detecting, or forecasting behavior can be directly transferred to one of the mitigation models. However, given that many models utilize unique data representation and output formats, creating a complete system can represent a serious undertaking. Developers must conduct further research in fields such as multi-modeling, model interoperability, and data fusion to generate models capable of manipulating the outputs of sociocultural understanding or predictive models into proper inputs for mitigation simulations in a standardized format.

Further, it is crucial to develop models transparent enough to foster trust by real-world users, without requiring them to become experts in computational modeling. A simulation system so complex that only an expert in computer science or mathematics can run it will not be effective for decision support of mitigation policies. Transparency can be facilitated through adequate training on how to apply these models and interpret the results when identifying possible COAs and analyzing their implementation in a particular sociocultural environment. However, significant research in human computer interaction is still necessary to determine how to design user interfaces for these computational mitigation models to ensure effective, intuitive use, and determine how best to incorporate them into the MDMP.

The final problem that affects all computational models described in this book centers on data. While many of these reasoning and simulation approaches are designed to handle large quantities of data, the outcomes will only be useful for discovering, analyzing, and comparing COAs if the input data (or the data used for the underlying models for understanding, detecting, and forecasting sociocultural dynamics) are reliable. For many social analyses, Internet social media present a new stream of human-generated data that may serve as an open source “sensor” providing insight into social processes. However, other tasks require data extraction from widely available, unstructured textual sources (news media, public statements, etc.) or qualitative information (interviews, surveys, etc.) collected through scholarly fieldwork or official human

intelligence channels. As Chapter 13 discussed in depth, integrating this wealth of information into computational mitigation models presents a major challenge.

7. Summary

This chapter has examined the potential for computational models to aid decision makers in developing, analyzing, and comparing possible COAs for mitigating sociocultural factors in the environment. Such tools have the potential to significantly ease the analytic and decision-making burden faced by humans in the field, allowing users to process large quantities of complex social or behavioral data that would otherwise be inaccessible. Using large-scale data analytics similar to those applied by companies such as Amazon or Google, these modeling frameworks can leverage the wealth of sociocultural information gained from understanding, detecting, and forecasting aspects of the human terrain. Mitigation models, therefore, can augment the existing MDMP, facilitating the development of robust COAs while also exploiting the expertise and knowledge of decision makers in the field. However, many of these enabling technologies are still in the early stages of research and development, and system developers must overcome significant technological and training challenges before mitigation models will become widely operational for real-world situations.

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15 Interactive data visualization for mitigation planning: Comparing and contrasting options[1]

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1. Introduction

Interactive data visualization can greatly assist decision makers in comparing and contrasting their options as they choose a course of action for mitigation. Admittedly, ineffective visualizations can lead to poor decisions (consider, for example, the many descriptions of unintelligible charts used in the process of deciding whether or not to launch the space shuttle *Challenger* (Tufte, 1997)). By contrast, effective visualizations can lead to a deeper understanding of the robustness of various courses of action, resulting in better outcomes for a greater proportion of decisions. In this chapter, we cover the underpinnings of effective visualizations that help decision makers better comprehend their options. Because using interactive visualization to compare and contrast courses of action represents a nascent area of study, we also discuss the research to date in this area and describe promising directions for future investigation.

1.1. Definition

In essence, visualization for mitigation means supporting option awareness. In this chapter, we use the definition of option awareness provided by Drury, Pfaff, Klein, and Liu (2013, p. 658): "… individual and team decision makers develop *option awareness* (OA): the perception and comprehension of the relative desirability of the available options, as well as the underlying factors, trade-offs, and tipping-points that explain that desirability…" Option awareness assists users in selecting a good course of action by creating an understanding of how effective that action will be under various conditions. This requires forecasting of plausible futures, starting with the particulars of a specific current situation. Ultimately, visualizations that promote option awareness should present the landscape of plausible outcomes for each option in a way that enables the user to easily compare those landscapes and choose the most robust option.

1.1.1. Types of decisions

Most visualization tools today simply present situation awareness data; the developers presume that the user will extrapolate from the details of a situation to decide on a course of action. This leaves all analysis of options and forecasting of outcomes to human cognition, with none of the burden carried by machines capable of analyzing many options quickly. Computer-supported option awareness alleviates this overload by presenting visualizations to augment cognition and increase understanding.

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As with situation awareness, individuals can achieve progressively higher levels of option awareness, and new interactive visualization tools can give decision makers much broader and deeper views of their options. Figure 1 shows the three levels of option awareness, with each level building on the insight and understanding gained from the previous level. A visualization that enables option awareness level 1 enables users to see and understand the comparative robustness of their options more rapidly. If the visualization enables option awareness level 2, users understand the key trade-offs between those options and the factors that make one option more robust than another. Option awareness level 3, which builds on levels 1 and 2, enables users to propose more effective options based on a deep understanding of relative robustness and the factors driving that robustness.

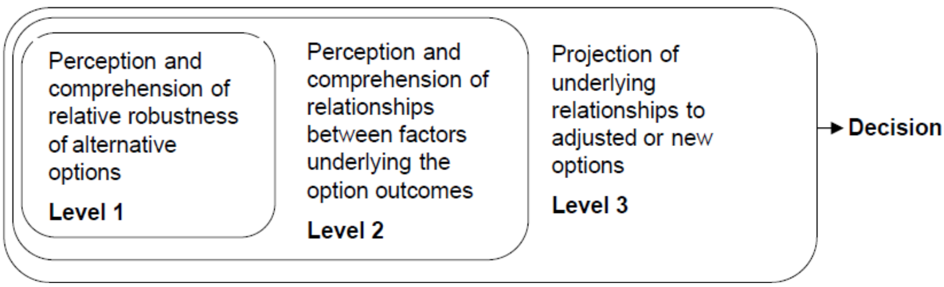


Figure 1. Levels of option awareness. Adapted with permission from Klein, Drury, Pfaff, & More (2010).

1.1.2. Types of data

A key driver for visualization in general and option awareness visualization in particular is the type of data to be visualized. Fundamentally, the option awareness data includes:

- A set of alternative options
- A set of conditions that can vary or are unknown (uncertainty)
- Criteria for evaluating the options
- Evaluation of the options

The evaluations can be generated by computer simulation or by a group of subject matter experts, or can be found from historical data. They result from examining each option across a range of possible conditions that could vary or may be unknown and measuring the outcome in terms of each relevant criterion (e.g., cost or lives lost). The complexity in option awareness data stems from:

- Options that are multi-faceted (e.g., the option has two aspects that may interact with each other in some way)
- Varying or unknown conditions, including aspects of the current situation (e.g., a flu outbreak with unknown lethality) or uncertainty about option effectiveness (e.g., what percentage of people will comply with a request to stay home from work)

Table 1 shows this breakdown for the simple notional dataset of the virus outbreak that we use as an illustration throughout this chapter. In this example, the decision maker must determine how to respond to the outbreak. The option has two components: (a) whether to implement social distancing (i.e., ask schools and workplaces to close) and (b) what percentage of the population to vaccinate (10% vs. 50%). These factors interact with each other because social distancing would result in fewer people becoming exposed to the virus, and thus vaccination would have less impact on the outcome. The uncertainty in this case comes from not knowing the deadliness of the new virus. Here we consider only three possibilities: 30%, 60%, or 90% of people exposed and not vaccinated will die from the virus. A real scenario would probably involve multiple unknown variables (e.g., unknown lethality + unknown percentage of the public that would comply with social distancing) and would require evaluation of tens to hundreds of possibilities (not just three). This would further complicate the data, resulting in an even greater need for effective visualization to aid the decision maker in understanding the robustness of each option and the underlying factors. In the illustrative example discussed in this chapter, the criteria we use to assess the goodness of each option are cost and lives lost.

Table 1. *Notional option awareness data: Most aggregation (top left) to most detailed (bottom right)*

		Criteria		
		Option	Single Weighted Score (i.e., Score)	Each Criterion Separately (i.e., Cost, Lives)
Uncertainty	Combined to Show Robustness (i.e., criteria includes set of values, one from each possible Deadliness condition)	Single Name (i.e., Option)	**Option Deadliness Score** OptionN10 <not shown {1, 33, 65} OptionN50 <not shown> {35, 53, 71} OptionY10 <not shown> {81, 85, 88} OptionY50 <not shown> {77, 79, 81}	**Option Deadliness Cost Lives** OptionN10 <not shown> {$34, $58, $82} {243, 486, 729} OptionN50 <not shown> {$63, $77, $90} {135, 270, 405} OptionY10 <not shown> {$37, $40, $43} {27, 54, 81} OptionY50 <not shown> {$76, $78, $79} {15, 30, 45}
		Each Aspect Separately (i.e., Dist, Vacc)	**Dist Vacc Deadliness Score** No 10 <not shown> {1, 33, 65} No 50 <not shown> {35, 53, 71} Yes 10 <not shown> {81, 85, 88} Yes 50 <not shown> {77, 79, 81}	**Dist Vacc Deadliness Cost Lives** No 10 <not shown> {$34, $58, $82} {243, 486, 729} No 50 <not shown> {$63, $77, $90} {135, 270, 405} Yes 10 <not shown> {$37, $40, $43} {27, 54, 81} Yes 50 <not shown> {$76, $78, $79} {15, 30, 45}
	Each Possibility Separately (i.e., Deadliness = 30, 60, or 90)	Single Name (i.e., Option)	**Option Deadliness Score** OptionN10 30 65 OptionN10 60 33 OptionN10 90 1 OptionN50 30 71 OptionN50 60 53 OptionN50 90 35 OptionY10 30 88 OptionY10 60 85 OptionY10 90 81 OptionY50 30 81 OptionY50 60 79 OptionY50 90 77	**Option Deadliness Cost Lives** OptionN10 30 $34k 243 OptionN10 60 $58k 486 OptionN10 90 $82k 729 OptionN50 30 $63k 135 OptionN50 60 $77k 270 OptionN50 90 $90k 405 OptionY10 30 $37k 27 OptionY10 60 $40k 54 OptionY10 90 $43k 81 OptionY50 30 $76k 15 OptionY50 60 $78k 30 OptionY50 90 $79k 45
		Each Aspect Separately (i.e., Dist, Vacc)	**Dist Vacc Deadliness Score** No 10 30 65 No 10 60 33 No 10 90 1 No 50 30 71 No 50 60 53 No 50 90 35 Yes 10 30 88 Yes 10 60 85 Yes 10 90 81 Yes 50 30 81 Yes 50 60 79 Yes 50 90 77	**Dist Vacc Deadliness Cost Lives** No 10 30 $34k 243 No 10 60 $58k 486 No 10 90 $82k 729 No 50 30 $63k 135 No 50 60 $77k 270 No 50 90 $90k 405 Yes 10 30 $37k 27 Yes 10 60 $40k 54 Yes 10 90 $43k 81 Yes 50 30 $76k 15 Yes 50 60 $78k 30 Yes 50 90 $79k 45

We follow visualization expert Ben Shneiderman's visual information seeking mantra of "overview first, zoom and filter, then details on demand" (Shneiderman, 1996, p.336) to make visualizations of the data more manageable for a decision maker. At the highest level, the data presented for each option includes the name of the option and a set of scores for each option. The top left cell in Table 1 shows the highest level of aggregation of the data: an overview. The two aspects of the option (dist and vacc) are combined into a name that describes the complete option (e.g., OptionN10). The two criteria (lives and cost) are combined into a single weighted score. The specific conditions under which each option was tested (i.e., the deadliness percentages of 30, 60, and 90) have been grouped by option, resulting in a set of values that represent the plausible outcomes for that option under uncertainty (the uncertainty about the deadliness of the virus). At the other end of the spectrum, as decision makers drill down to obtain more details, they would move toward the bottom right cell in the table, which shows the highest level of detail for this simple example dataset.

The characteristics of the data constrain the space of relevant visualization techniques. Users can attain option awareness level 1—understanding the robustness of each course of action—even from the most aggregated form of the data, the overview, if visualized effectively. However, displaying only the aggregate data hides the underlying factors that drive robustness. To achieve level 2 option awareness users require a capability to interact with the data, filter the data to show only the most worthwhile options, and drill down into the data to find more details so they can begin to understand the factors driving the outcomes. This helps users to understand the trade-offs: for example, two options may have a relatively similar average outcome, but one has a much better best case and much worse worst case than the other.

1.2. Why Visualization Matters

The visual interface constitutes the last gateway between data about the robustness of the options and the decision maker's mind. A clear presentation of the option awareness data reduces the cognitive burden. However, if the chosen visualization technique obfuscates options and outcomes, decision makers will find it difficult to fully comprehend the resulting analysis of their options.

Designers must create cognitively and perceptually effective visualizations that allow the user to interact with the visualization in appropriate and meaningful ways. Something as simple as the terminology used to convey the data can affect risk perception and the resulting decisions (e.g., due to the framing effect) (Ancker, Senathirajah, Kukafka, & Starren, 2006). Further, if users do not understand the inner workings of a tool, particularly a modeling and simulation tool, they may blindly trust the tool too much or lose trust in the tool altogether (Sheridan, 2002). To realize the powerful benefits of using interaction visualizations to analyze options, new visualizations and visual analytics tools must effectively address these types of cognitive issues.

1.3. What Makes Visualization Difficult

Option awareness visualization comes with its own unique set of challenges that future research must address. At a high level, some of the challenges in this space include:

- Complexity of the data

    - Achieving greater levels of option awareness will require visualizations that provide deeper understanding of the underlying, inherently complex data. How do we effectively portray the robustness of each option? How do we create visualizations that clearly show users how the different factors interact?
- Diverse users without statistics backgrounds
    - As this chapter will show, statistical analysis and concepts such as mean and standard deviation are often used to summarize the set of scores that represent the robustness of an option (e.g., in the example above, OptionN10 has a set of scores {1, 33, 65}). Yet many decision makers do not have a statistics background. How do we create interactive visual analytics tools useful to groups of stakeholders who have diverse backgrounds and experiences? Which information could and should the visualization abstract away?
- Need for effective visualization design principles to enable trustworthy, defensible decision support
    - Much has been written about creating effective situation awareness displays, but little about creating effective option awareness displays. Rigorous design principles will lead to visualizations that effectively support option awareness. Further, in the context of selecting between options, good design principles are important not just for cognitive and perceptual reasons, but also for:
        - Ensuring appropriate levels of trust – While decision makers will not rely exclusively on a visual analytics tool for information, that tool will be one of several sources. Decision makers need a way to determine the reliability of the results and the level of trust to put in what they are seeing.
        - Ensuring ethical designs – Designers must create visualizations that show the data in a way that does not unduly influence the user's decisions.
        - Ensuring defensible results – Option awareness level 2 gives decision makers the understanding they need to explain or defend the reasons why they chose one option over another.

The remainder of this chapter presents more details on these challenges.

1.5. How Visualization Fits into the Bigger Picture

This chapter centers on visualization for comparing options and gaining understanding of the trade-offs, but comparing alternative options represents only one step in the mitigation process. In reality, visualization can help in other areas related to mitigation; for instance, in generating alternative options, assisting those tasked with executing the selected option, or monitoring the effectiveness of the selected option.

First, a subject matter expert needs to identify and generate alternative options – whether proven or novel – before they can be modeled and compared. Most real-world cases fall into the middle of this continuum. Well-known options typically involve checklists and well-documented processes. Visualization can allow users to compare all of the options and can create the basis for generating new variations. By observing which factors lead to good or bad outcomes, a user acquires the basis

for creating new, even more effective options. Visualizations that provide option awareness levels 2 and 3 assist with this process (see sections 3.1.2 and 3.1.3 in this chapter).

Second, once decision makers select a particular action they must prescribe how to execute the action. The individuals responsible for carrying out the action will need detailed instructions. The details must include what to do and how to do it, and may require discussion and revision (e.g., the Postal Service may be asked to deliver vaccines to homes). Those responsible for carrying out the action must also know what resources will be available to support the action (e.g., how much vaccine to deliver) and the scope of the action (e.g., to whom to deliver the vaccines). Visualization could help decision makers communicate this type of information to the action takers.

Third, as the actions take place and the situation evolves, decision makers must assess the results and adapt the response based on that assessment. For example, if people are asked to stay home from work, someone must determine what percentage of the public is complying. The greater the percentage of people who comply with what is asked, the more effective the option. This calls for practices and tools that enable the initial data and the reasons for selecting a particular option to be available when assessing the effectiveness of the actions being taken. This would contribute to effective mitigation because decision makers could better understand how well the situation on the ground matched the predictions of the original models used to choose among options. All of these areas call for research, including work to build a system that provides early indicators of how well the mitigation actions are working.

We limit the scope of this chapter to visualization for comparing the relative robustness of a set of options, understanding the trade-offs between those options, and gaining a deep enough understanding of those factors to generate novel options. The assessment phase represents a full circle back to using visualization for understanding and detection. In the remainder of this chapter, we first briefly describe how decision makers use option analysis today, which leads into the discussion of the state of the art. We then discuss areas that require more research to further advance the state of interactive visualization tools for option awareness.

2. State of the Practice

This section summarizes the primary techniques used for visualization today, highlights some findings, and suggests shortfalls in current capabilities.

2.1. Manual Techniques

Today, most analysts compare different options by hand, perhaps with the assistance of a spreadsheet to capture the data, and then visualize the results in a simple static diagram that can be placed on a presentation slide. For example, in its Analysis of Alternatives (AoA) Handbook (AFMC, 2008) the Air Force includes a section on presenting the results of the AoA, as illustrated in Figure 2. This type of chart is sometimes referred to as a horse blanket because of its colorful design.

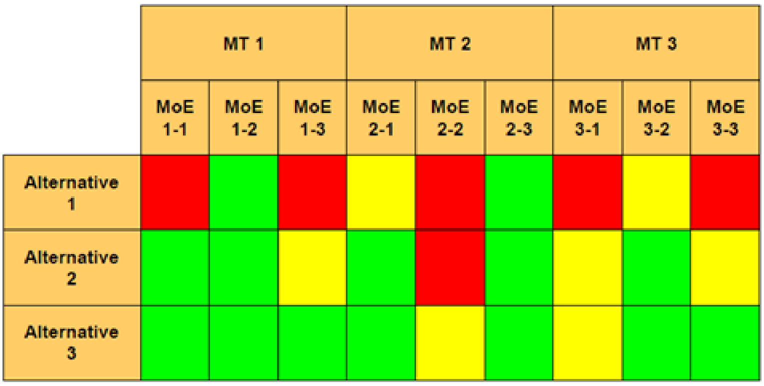


Figure 2. Horse blanket – static visualization for comparing options (AFMC, 2008).

The AoA Handbook uses this horse blanket (or heatmap) visualization approach to compare options ("Alternative 1," etc.) across a number of different conditions ("MT 1" is Mission Task 1), for a number of different criteria ("MoE 1-1" stands for Measure of Effectiveness, a measure relevant to the first mission task). The handbook stresses that designers must apply a method for mapping colors based on the score relative to a meaningful threshold and discourages use of weighted averages across criteria, as these can be misleading. If we apply this static visualization to our example dataset shown in Table 1 we obtain the visualization in Figure 3. Each cell shows the average value.

Figure 3. Horse blanket (heat map) applied to notional virus outbreak dataset.

The simple example in Figure 3 reveals the drawbacks of this visualization method. By showing only the average values, it does not indicate robustness across plausible deadliness percentages (e.g., best and worst case values for each option). This means it does not provide option awareness level 1. Since it does not show the robustness, it also cannot show the factors underlying that robustness. Additionally, users have no easy way to interact with, filter, or drill down into the data to explore the relationships among factors and thus to achieve option awareness level 2. Section 2.2 briefly discusses a few emerging visualization techniques used to achieve option awareness.

2.2. Interactive Techniques

In addition to the static visualizations found in presentations, there are commercial software products that provide interactive visualizations for comparing options. These interactive tools tend

to depend heavily on different analytic techniques. Some of these tools provide some support for option awareness level 2, in which a person understands the factors underlying the outcomes. Sensitivity analysis and classification trees are two examples of techniques found in these products.

Sensitivity analysis allows users to determine how much of the variance in the outcome is due to different sources of uncertainty. For example, based on the data in Table 1, the variance in the set of scores associated with each option results from the choice of whether to implement social distancing, the choice of how much of the population to vaccinate, and the deadliness of the virus.

The simplest approach to sensitivity analysis involves varying a single condition at a time and examining the impact on the outcome. Tornado charts show the results of this approach. For example, in the tornado chart in Figure 4, the occupancy rate of schedule flights (i.e., capacity of scheduled flights) was varied from 40% (worst case) to 60% (best case). The chart shows that if occupancy is at only 40% the airline will lose money; however, if occupancy hits 60% the airline will profit by approximately $35,000 annually. The sort order places the variable that causes the most variance in the outcome on top. In this example, the occupancy of scheduled flights has the greatest influence on the annual profit while the cost of insurance has the least.

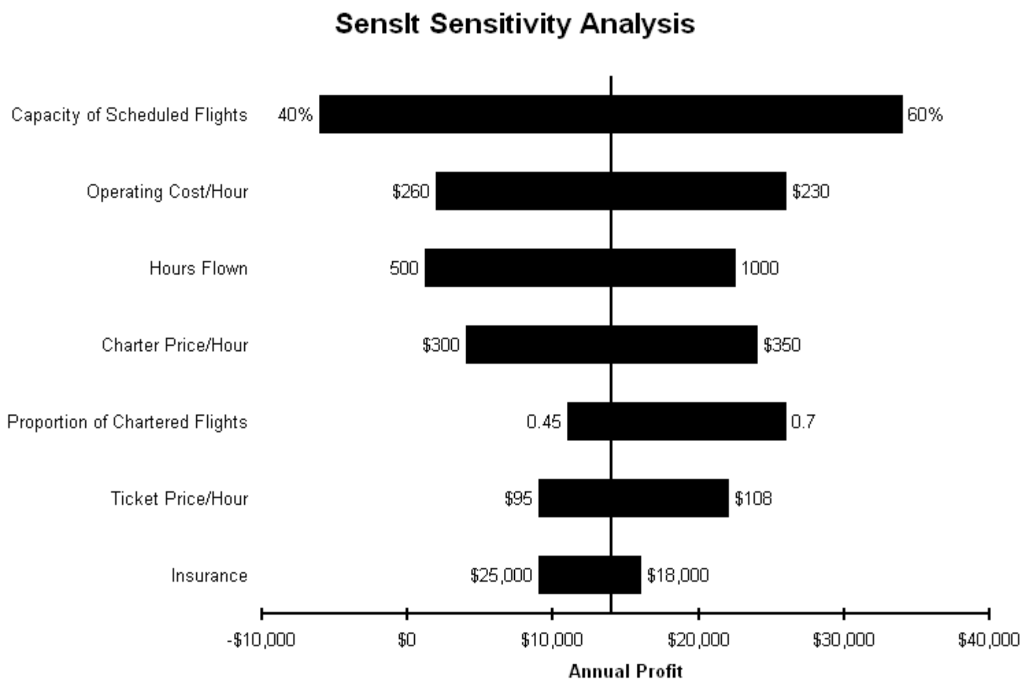


Figure 4. Tornado chart. Adapted with permission from Sensit (2013).

Sensitivity analysis shown in tornado charts falls short on option awareness level 1. Since each factor is varied independently, the analysis involves a single notional scenario rather than values from multiple varying or uncertain conditions. However, such charts do start to provide option awareness level 2 by showing the factors that have the greatest impact on the outcome. For

example, if we consider our notional example from Table 1, our tornado chart would look like Figure 5 for a worst case scenario. The effect of each factor (Dist, Vacc, Deadliness) on the total number of lives lost clearly identifies social distancing as the most important factor because it changes the percentage of the population exposed to the virus. It does not show interaction effects (i.e., that if social distancing is implemented the percentage of the population vaccinated matters less), but does provide a simple method of ranking the importance of the underlying factors. The need remains for specific visualization approaches that could begin to explain conditions under which a particular option will produce a better or worse outcome.

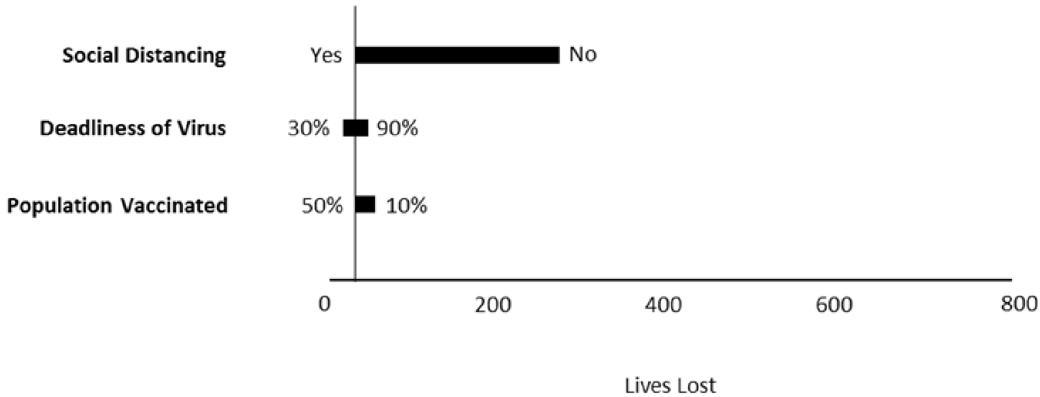


Figure 5. Tornado chart showing notional virus outbreak dataset.

A full summary of all the commercial solutions is beyond the scope of this chapter. The example in Figure 4 came from SensIt, an add-on for Excel. Other companies, such as Vanguard Software, have similar software solutions for generating non-interactive visualizations.[2] We mention them purely as examples of existing commercial software that represents the types of visual analytics tools that will eventually support users in achieving progressively higher levels of option awareness.

Another interactive visualization technique that aids in reaching option awareness level 2 is a decision tree. The data mining algorithms that produce classification trees can generate decision trees that bin the outcomes into categorical groups (e.g., good, moderate, and poor outcomes). The leaf nodes in a tree visualization show the number of good, moderate, or poor outcomes that resulted from following a particular path down the tree. Figure 6 gives an example for the notional virus dataset, showing that the decision to implement social distancing was the most crucial factor in ensuring good outcomes. Social distancing led to the fewest number of lives lost, regardless of the percentage of the population vaccinated or the deadliness of the virus.

[2] See http://www.vanguardsw.com/products/vanguard-system/risk-analysis.htm

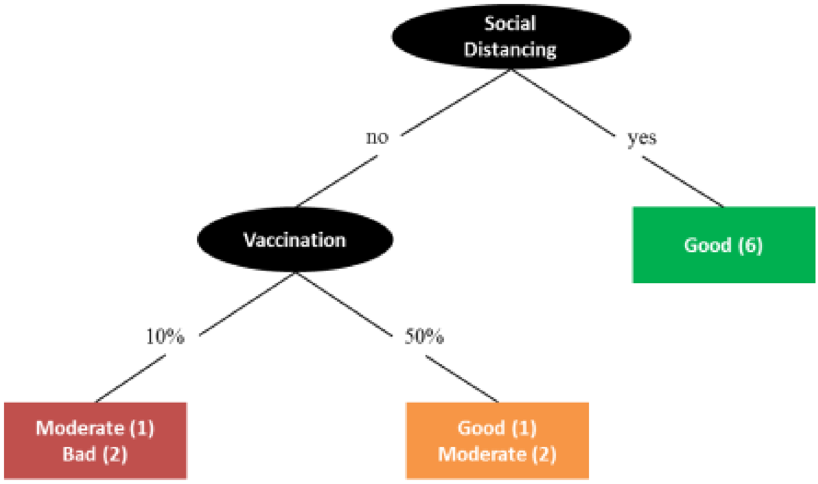


Figure 6. Decision tree showing option awareness level 2 for notional dataset's number of lives lost.

The factors that have the most influence on the outcome appear at the top of the tree. This approach helps explain the factors behind a particular outcome. As in the case with the manual techniques, much work remains to support option awareness effectively.

2.3. Lessons Learned from Practice

Readers must keep in mind that while this chapter uses a small, simple, notional dataset for illustrative purposes, in practice the source dataset can be large and complex. The scalability of the visualization techniques and interaction with the visualizations must enable display of large complex datasets in ways that domain experts can quickly understand. Often the complexity involved means that people resort to very simplistic stoplight chart indicators (as in the horse blanket), consider only a single scenario (as in the tornado chart), or show only the best and worst cases for a given option.

2.4. Gaps

Better interactive visualization tools, especially those that appeal to domain experts, are needed to bring these capabilities to an audience without a strong background in statistics. Users need tools that can enable all three option awareness levels and provide a seamless transition between levels. These tools must be accessible for end users, with appropriate training on basic statistics and advanced visualization techniques where necessary. Research is just beginning to address some of these issues.

3. Visualization Techniques for Option Awareness

While existing visualization techniques can show the necessary types of data, using these techniques to visualize option awareness data represents a new direction. In this section, we describe a few techniques that developers could incorporate in future tools to promote option

awareness levels 1 and 2. How well visualization can enable and support option awareness level 3 remains an open question.

3.1. Option Awareness Levels

3.1.1. Option awareness level 1 – Showing distribution

Option awareness level 1 requires tools that show the relative robustness of each option. This means displaying the set of plausible outcomes for each option. The challenge for option awareness level 1 lies in showing the distributions of outcomes. Designers and developers must determine how much statistical analysis is needed and appropriate for the audience and what can be simplified.

Visualization Approach

Box plots, also known as box-and-whisker plots, are a statistical visualization technique created by Tukey (1977). There are many variations of the box plot; a basic plot is shown in Figure 7.

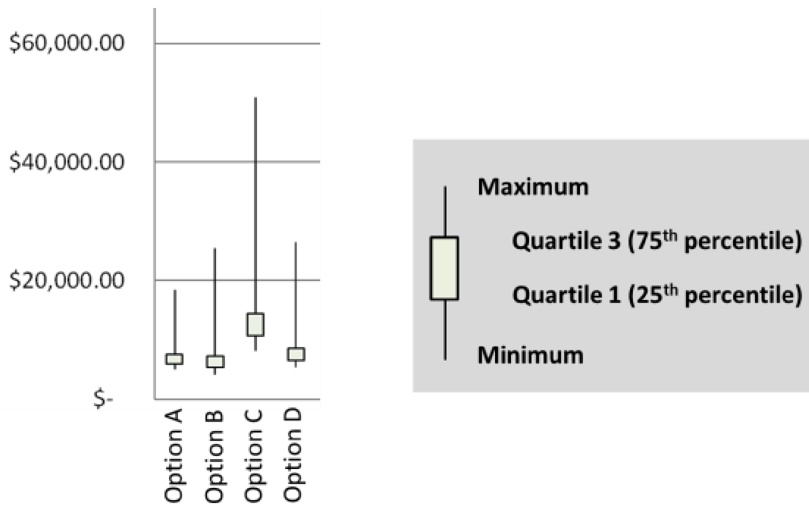


Figure 7. Box plot showing distribution of plausible futures (option awareness level 1) for four options.

Data

Each of the four notional options (Options A, B, C, and D) in the dataset had 35–40 possible outcomes in the dataset represented in Figure 7. The algorithms calculated the minimum cost possibility, maximum cost possibility, first quartile, and third quartile.

Encoding

The vertical line represents the range from the best case to worst case. The box in the middle shows the middle 50% of all plausible outcomes for that option (i.e., the 25th–75th percentile).

Interaction

Users may wish to sort data based on the compactness of the range of plausible outcomes (length of the line), the best outcome (bottom of the line), the worst outcome (top of the line), or the characteristics of the middle 50% of plausible outcomes (size of the box, top or bottom of the box).

Advantages and Disadvantages

The box plot provides an excellent statistical summary of the data, allowing users to compare best, worst, or most likely outcomes under uncertainty. However, users must understand the concepts of the 25^{th} and 75^{th} percentiles and basic statistics to interpret the plot.

Alternative Visualizations

There are many alternative visualization techniques that show the actual values rather than a statistical summary of distribution, as well as many variations on the basic box plot. The most basic alternative technique is the histogram. Figure 8 shows the landscape of plausible outcomes and provides option awareness level 1. The challenge in developing such a histogram is to appropriately bin the data into groups (e.g., $4,000–$4,999 is a bin). A wise selection of bins can create an effective way to show option awareness level 1 using the actual data points rather than statistical summary data.

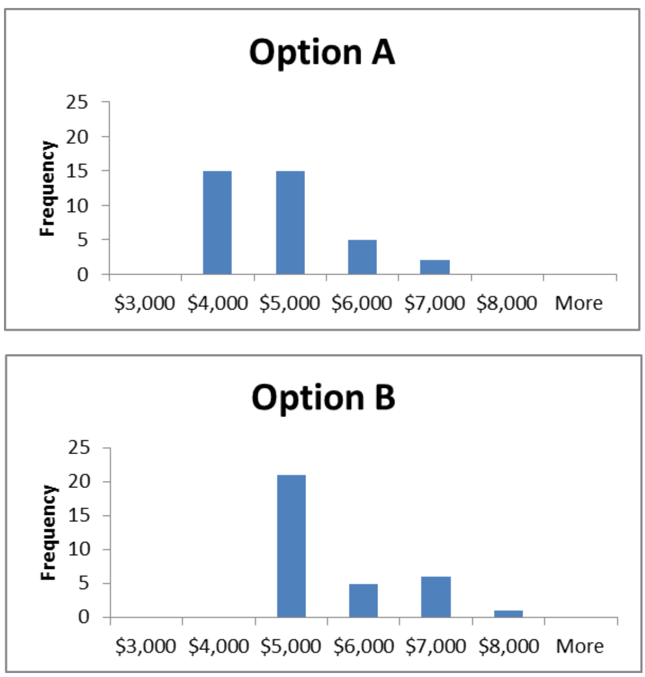


Figure 8. Histogram showing landscape of plausible futures.

Variations of the box plot show values in addition to the statistical summary data. These variations include density plots, density plots with a rug, bean plots, and violin plots; Yau (2013) gives a brief tutorial on these plots and how to implement them using the programming language R. Bean plots show all of the specific data points while addressing the issue of overlapping points. Other

proposed techniques include showing all outcomes as lines, but making each line semi-transparent to reveal where many points are superimposed on each other (Barnes, 2013).

Some past work has compared these visualization designs and discussed the trade-offs among different visualization techniques for showing the distribution of values (Ibrekk & Morgan, 1987). The main takeaways were that simple explanations of the visualizations aided understanding, but only minimally, and basic visualization techniques like box plots or the semi-transparent approach offered particular promise. Visualization techniques for showing distribution of values have seen little adoption, perhaps because of the need for users to understand basic statistics. Future research should address the comparative effectiveness of these techniques to support option awareness and gain adoption.

While all the examples provided may lead to option awareness level 1 because they show the data distribution, they do not provide insight into the underlying factors that caused the difference in outcomes. That insight requires effective multidimensional visualization techniques that show the relative importance of factors that result in good or bad outcomes for a particular option.

3.1.2. Option awareness level 2 – Showing multidimensional data

Option awareness level 2 requires a way to display the underlying factors driving the outcomes and the interactions among those factors. In our simple notional dataset, this means we need a way to effectively understand the impact that social distancing, vaccinations, and deadliness of the virus have on the outcomes. We also need to know how those variables interact. Additional benefits of visualizing the factors include that showing users what factors affect better vs. worse outcomes provides a foundation for developing new courses of action (see section 3.1.3). Furthermore, users can immediately see the sources of uncertainty and can then question the underlying assumptions made in the models. Moreover, seeing the factors can help users compare the relative importance of each source of uncertainty in a given situation. The challenge for option awareness level 2 lies in showing the most critical factors and the relationships among them. In many datasets this challenge is further compounded by a large number of variables.

Visualization Approach

A key visualization technique in this area is the decision tree, classification tree, or variant of it (see section 2.2 and Figure 6).

Data

The data includes all of the plausible future paths for all of the options and the corresponding outcomes.

Encoding

Some of the nodes in the tree represent a decision point (e.g., whether to implement social distancing) or variable (e.g., deadliness of the virus). The decision points or variables with the greatest impact on the outcome appear higher in the tree. The leaf nodes at the lowest level of the tree structure represent the outcomes. Nodes can be combined and aggregated in cases where a variable has no influence on the outcome. For example, if social distancing is implemented then the outcome will always be good, regardless of vaccinations or deadliness, so the nodes under yes to social distancing can be collapsed into a single node that represents good outcomes.

Interaction

Users may wish to filter the data so that only paths that lead to good outcomes are shown in the tree. They also may wish to prune the tree by selecting a value for a particular option (e.g., no to social distancing).

Advantages and Disadvantages

While decision trees can prove highly effective in aiding option awareness level 2, they can become complex when a situation involves many variables. Users may require training to become familiar with the underlying analysis and understand what the tree shows. To attain option awareness level 2, users need new, easy-to-grasp visualizations that show the interactions among factors and the impact they have on the outcomes (i.e., that display the data from all plausible futures, not just one).

Alternative Visualizations

There are alternative visualization techniques, techniques other than decision trees, which can assist with option awareness level 2. These techniques for visualizing multidimensional data include a scatterplot matrix and parallel coordinates. A full discussion of approaches for multidimensional data visualization, which would help in establishing option awareness level 2, is outside the scope of this chapter. We cover this topic briefly only to help the reader understand what research has already accomplished and where open research challenges remain.

3.1.3. Option awareness level 3 – Identifying new options

Once users have option awareness levels 1 and 2 they will understand the factors underlying the outcomes for a particular option(s) and will need a way to create a new option and confirm the predicted robustness of that new option. Creating a new option calls for a capability to specify options not previously considered (e.g., apply quality assurance to a vaccination program to ensure a minimum vaccination level). Interaction controls could help achieve option awareness level 3 provided they feed new option information back to level 1 or 2 visualizations.

3.2. Gaps

While visualization and interaction techniques can move us one step beyond the current state of the practice, the biggest gains would come from (a) new visualization techniques that provide option awareness level 3, (b) visualizations for option awareness that are easy for non-statisticians to understand and use, (c) tests of the effectiveness of these new techniques for supporting selection of options in the real world (e.g., which multidimensional visualization techniques best support selection of an option and aid understanding of factors underlying the option's robustness), and (d) an integrated capability for achieving progressively higher option awareness levels (e.g., bringing together option awareness levels 1, 2, and 3). Further research is needed to understand how well existing techniques work when used in real-world situations where the uncertainty would decrease over time and the option awareness data could be refined in real time. This calls for visualization methods that clearly show users where, how, and why the robustness of options has changed.

4. State of the Art

In this section we focus on the most recent advances and highlight cutting-edge research on visualization for option awareness. Because these techniques are new, much remains to be done to confirm their effectiveness. In the coming years, however, these capabilities should make their way into the operational community.

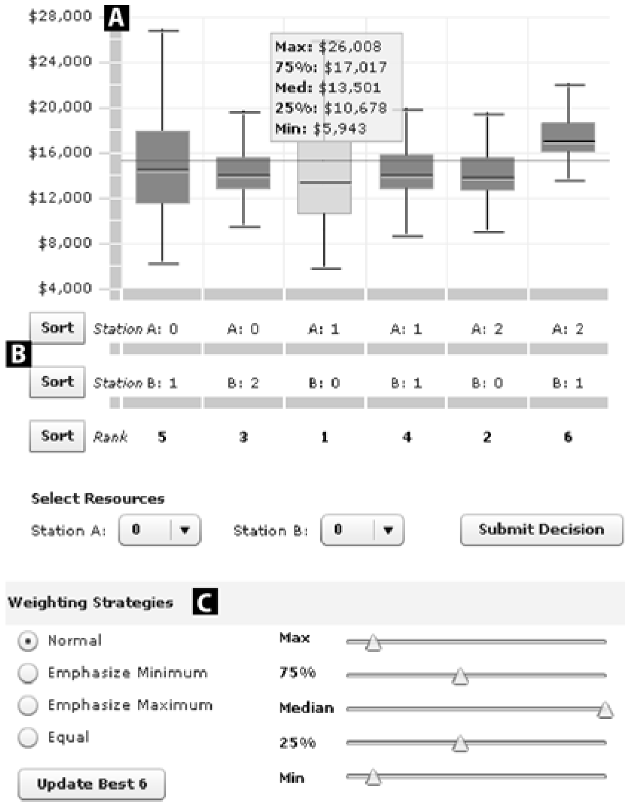
4.1. Areas of Active Research

While researchers have produced many systems over the years to increase situation awareness, the distinction between visualization needed for situation awareness versus option awareness is still emerging. Significantly less effort has centered on visualizing the robustness of different options and interacting with the option awareness data in a meaningful and comprehensible way. The research literature in this area is very recent, and scanty.

We first discuss design principles proposed for effective option awareness and some new interaction and visualization techniques. We then present research on bringing option awareness visualizations to a broader audience (to users with strong domain knowledge who may not be statisticians).

4.1.1. Design principles for effective option awareness visualizations

Researchers have developed many design principles to undergird situation awareness visualizations (Endsley, Bolte, & Jones, 2003). However, Drury, Pfaff, Klein, and Liu first proposed a set of visualization design principles to support option awareness (Drury, Pfaff, Klein, & Liu, 2013). These principles emerged from multiple experiments. Figure 9 gives an example of an interactive box plot visualization used in some of these experiments.



User interface example showing (A) frequency distributions of outcomes for top six options, (B) sorting by rank or quantity of resources, and (C) controls to customize the weighting strategy used to rank options, including four presets.

Figure 9. Option awareness visualization used in experiments informing design principles. Adapted with permission from Drury, Pfaff, Klein, & Liu (2013).

Drury et al.'s design principles are both interaction oriented (i.e., allow users to specify the values for the input parameters, to add their own weights to each criterion, and to filter data and sort options) and visualization oriented (i.e., show only the top few options and show the outcome under a variety of conditions rather than a single set of most likely conditions). Their contributions and insights cover much of option awareness level 1 and just begin to address option awareness level 2. These represent the first visualization design principles specifically designed for option awareness, and will surely evolve as option awareness concepts become more widely adopted and researchers learn more from real-world use of their models and visualizations.

4.1.2. New interaction and visualization techniques

As described in section 3, many new visualization capabilities have begun to emerge in the field of visual analytics. These capabilities align nicely with some of the underlying needs in the area of option awareness, as visualization of uncertainty is an essential part of option awareness. These interactive visualizations provide new mechanisms for achieving option awareness. However, much remains to be done to effectively visualize option awareness data.

In the remainder of this section we describe some visualization techniques that reflect the latest thinking about visualizing uncertainty: a capability essential to achieving option awareness. Heinzl (2012) gives a sampling of the latest visualization and interaction techniques, some of which could be used to obtain option awareness level 1 because they relate to visualizing the distribution of values. Others provide an analysis of the parameter space – a type of visualization that closely aligns with option awareness level 2 and with understanding the factors underlying the robustness of each option.

Most of the latest techniques related to option awareness level 1 extend or combine previously known techniques. Pang's (2012) perspective on the field of uncertainty visualization covered visualization techniques such as histograms, box plots, uncertainty glyphs, embellishments, pseudo-coloring, transparency, and fuzziness and dust clouds. Potter (2012) described visualization techniques that directly relate to option awareness level 1 and visualization of the distribution of values, such as error bars, spreadsheets, and many variations on box plots (including additions for aesthetics, value prevalence, sample size, confidence levels, moments, and modality). The newest visualization technique she discussed was the summary plot (Figure 10) which combines four related plots into a single plot that presents more information than any of the visualizations would alone. Potter, Kniss, Riesenfeld, and Johnson (2010) describe the summary plot as an advanced visualization technique that experts could use to more fully understand the robustness of each option. Such plots yield even more information on the comparative robustness of different options to viewers with a strong statistics background. However, as Potter points out, users need new visual metaphors to help visualize uncertainty.

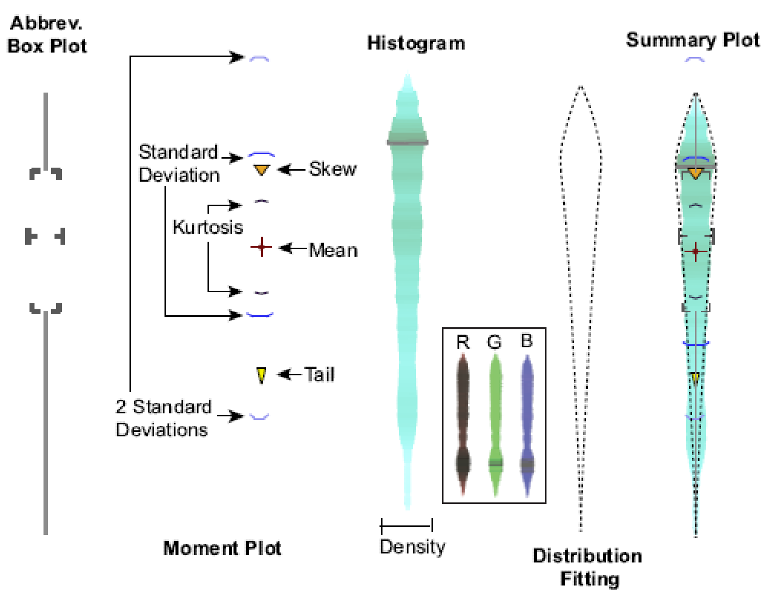


Figure 10. Summary plot. Adapted with permission from Potter, Kniss, Riesenfeld, & Johnson (2010).

The latest visualization techniques related to option awareness level 2 tend to center on the interactions among multiple linked views of the data. A good example of this additional interaction is Heinzl's (2012) visualization, which assists car designers in such tasks as selecting the fuel injection timing and engine speed in order to meet their targets with respect to torque and fuel consumption. The visualizations used include scatterplots and parallel coordinate plots with box plots overlaid, and incorporate multiple linked views. Figure 11 shows examples of these visualizations. Note that the visualizations in this example show multiple aspects of the option to be selected and two criteria for evaluating the goodness.

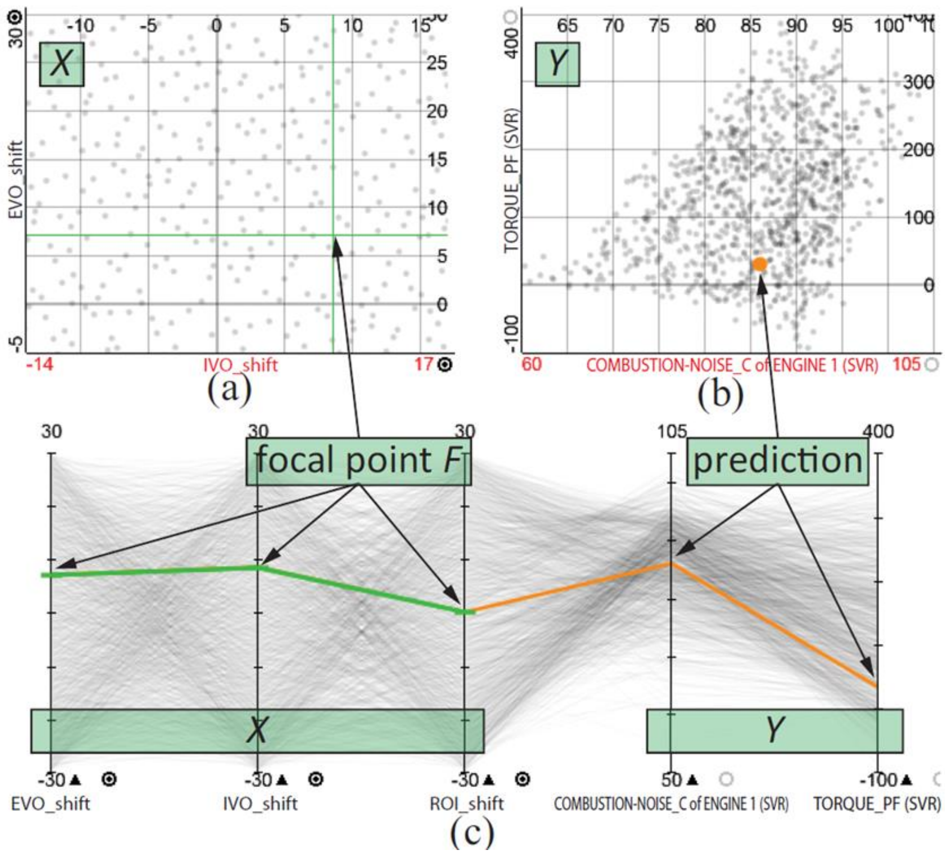


Figure 11. Scatter plots and parallel coordinate plots used for car design. Adapted with permission from Berger, Piringer, Filzmoser, & Groller (2011).

Some researchers have begun to address ways of promoting better understanding of the space of possible futures as a scenario plays out over time. One tool, World Lines, does this by using a horizontal tree visualization below a timeline (Waser, Fuchs, Ribicic, Schindler, Bloschl, & Groller, 2010). As the user selects a new action to try at a particular point in time, a new branch grows out of that tree. The user can see multiple scenarios (branches in the tree) in a single view and

compare how they develop over time. The authors use the example of a flooding scenario in which users must decide how to place sandbags in a way that minimizes the number of flooded buildings and uses as few sandbags as possible. World Lines does not necessarily provide option awareness level 1 or 2, since it does not show the robustness or factors underlying the goodness of the chosen options. However, it does allow users to steer the modeling by specifying input parameters at particular points in time and to try new scenarios. This may begin to provide support for option awareness level 3. The tool also represents a step toward an ability to provide more information on the temporal dimension of option awareness data. Future research should explore this area further.

Most of the tools described in the research literature are best suited for experts with statistical knowledge. Engineers can use these interactive visualization tools and approaches, but the domain expert would require training on a number of different statistical concepts to understand the resulting visualizations. In the next section we examine how innovative tools might reduce the necessary training and provide more intuitive visualizations that would help make option awareness more accessible to domain experts who do not have a background in statistics.

4.1.3. Bringing capabilities to a wider audience

Visualization could greatly assist decision makers who could benefit from understanding the robustness of their options but aren’t statisticians. The visualization community has recently recognized the importance of filling this gap because more and more mainstream audiences now use interactive visualizations. In fact, a recent master’s thesis (Danziger, 2008) described creating “Information Visualization for the People” to address these opportunities.

Media organizations provide a source of inspiration. News media must rapidly build visualizations that a diverse population can easily interact with and understand. For example, the *New York Times* and *Washington Post* now have interactive visualization departments. The *Washington Post* recently published one such visualization (Andrews, Cameron, & Keating, 2013). This interactive visualization could inspire future option awareness level 1 visualizations because the data has the characteristics needed: a distribution of values (for a given medical procedure). The equivalent data in our example relates to the distribution of outcomes for a given option. In the *Washington Post* visualization, they chose to show the lowest value, highest value, and average value. By selecting a particular state from the drop-down menu at the top, users can see where a particular state appears in the distribution, revealing how that state compares to the others in terms of being closer to the minimum or maximum or closer to the average.

A second example, this one from the *New York Times*, provides a visualization that could serve as an inspiration for providing option awareness level 2. The *New York Times* created this visualization (Bostock & Carter, 2012) in the Fall of 2012 during the U.S. presidential race. The example shows the rough equivalent of an interactive decision tree. A user can drill down into the data by mousing over paths in the tree to obtain more detail, and can filter the data by selecting a particular path or by selecting the outcome in a particular state shown at the top. The filtering prunes the tree to show the remaining paths to victory for each presidential candidate. Similar visualizations and interactions could provide level 2 option awareness to users if populated with different data.

These visualizations, particularly in their interactive form, increase the understandability of complex data, thus reducing the human cognitive bottleneck. The data may be complicated, but the visualizations need not be. Researchers must apply this approach of simplifying complex data as much as possible, but no more, to option awareness so that the visualizations can be used by a wider audience. News media organizations such as those mentioned here probably have especially valuable information regarding how much to simplify an analysis to make the process clear to the average person who does not have a strong statistics background.

However, research must still determine the effectiveness of such visualization techniques in the context of supporting robust decision making. To generate option awareness, decision support scenarios may call for more complex information than that used in the examples above. Nonetheless, these visualizations provide important examples of techniques that do not require explanation and instead enable users to focus only on understanding the data. The key is to find an appropriate balance.

4.2. Gaps

All of the option awareness concepts, new visualization design ideas, the ability to simplify those designs, and the underlying design principles are evolving and would benefit from greater insight. New, more effective visualization techniques are needed for all levels of option awareness, particularly for level 3. The design principles must evolve together with the concepts and practice, based on use in the real world. Research should also seek to develop methods for bringing all three levels of option awareness together into a single integrated tool: one that allows users to progress easily from one level of option awareness to the next. As the basics evolve, these visualizations must eventually be adapted to extend beyond the desktop to visualizations appropriate for decision makers who use tablets or mobile devices to display data; in other words, to move the capabilities out of command center-like environments and into the hands of users in the field.

5. Call to Action

To bring the new technologies and methods into operational use all of these techniques must coalesce and the emerging set of design principles must evolve. Widespread use of visualization tools depends on advanced design principles based on observations made in the field rather than only in a laboratory.

In addition to systems based on these advanced visualization design principles, users will need to understand the underlying analysis that generated the data shown in the interactive visualizations, and will need to be trained on how to apply these visualizations for decision making. User training and experience, combined with better design principles and tools, could avoid many potential pitfalls in the use of visualizations. Further, as visualizations evolve, researchers must determine how much to simplify the complexity of the underlying analysis and visualization techniques. Effective visualizations must achieve a balance between supplying enough detail to support good decisions while not displaying so much detail that users dismiss the tools as too complex.

In the meantime, developers should seek to smooth the transitions from situation awareness displays into option awareness displays. Tools are also needed that allow users to progress from

one level of option awareness to the next. As a situation plays out some of the uncertainty will disappear, which calls for rapid feedback into the tools to update underlying assumptions and uncertainties. Option awareness visualizations must also update option comparisons as uncertainty decreases to help users know when to adapt their mitigating actions as a situation evolves.

The future of option awareness visualization is wide open, with research only starting to focus on option awareness as a distinct concept. Realizing these capabilities in future visual analytics tools offers great potential benefits to decision makers faced with uncertainty.

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16 Enabling operational users to fully exploit the tools, data, and analytics to shape potential futures[1]

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1. Overview

Human, social, cultural, and behavioral (HSCB) modeling with forecasting and mitigation-option capabilities improves operators' ability to understand and shape the operational environment. Sociocultural data and analysis assist in the identification of crises further "left of bang," allowing consideration of more mitigation options and more time to assess possible ramifications (Flynn, Sisco, & Ellis, 2012). As a greater number of HSCB-driven mitigation technologies improve and are deployed, more operational users will require training on these tools, data, and analytics to mitigate and shape potential futures.

Limited time, tools, and capacity currently constrain the number of prospective courses of action (COAs) that operational planners can generate and assess as they try to mitigate or avert potential crises. Processes implemented today are highly manually intensive and seldom integrated (computationally) with HSCB knowledge. As HSCB-driven mitigation technologies continue to evolve at a rapid pace, the quality and kind of information made available to users and the potential utility of this content will begin to blur the traditional "lanes" between current career fields such as intelligence, operations research, and operational planning. This, in turn, will require innovations in training to prepare users to effectively recognize and leverage content relevant to analyzing COAs for mitigation. For example, training on model interpretation, typically concentrated in particular career fields such as operations research, must be expanded to ensure that more operational users can effectively apply emerging mitigation options.

As the proliferation of HSCB knowledge makes COA mitigation capabilities more accessible, innovative training for the skills and knowledge needed to perform COA mitigation tasks becomes imperative. This chapter focuses primarily on the mitigation tasks related to COA development, COA analysis, and COA assessment. For each key mitigation task, trainers must consider user skill (ability necessary to perform the task) and knowledge (facts, concepts, and principles required to perform the task), as defined in the Military Handbook 29612-2A (MIL-HDBK-29612-2A, 2001). An initial analysis of the functional tasks involved in mitigation highlights several considerations, such as key training objectives and ideal training formats (e.g., computer based training, classroom, or exercise).

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This chapter begins with an overview of the HSCB knowledge and skills necessary to perform mitigation. We present a use case detailing the processes involved in development, analysis, and assessment of COAs. From the context generated by the use case, we describe training for mitigation by addressing training for each of those processes. We present each of the processes in terms of the knowledge and skills needed, the implications for training, and the state of the practice.

1.1. Knowledge and Skills for Mitigation

In general, HSCB knowledge and the skills for acquiring, understanding, applying and maintaining it can facilitate each mitigation task. HSCB knowledge spans general sociocultural information, such as current and historical characteristics of a geographic region (country, city, village, etc.), groups, and even individuals. This information builds context for and supports computational social science and other analytical capabilities designed to anticipate the effects (including n^{th}-order effects) of particular COAs and assess their impact. It also provides greater context to enable mitigation of a forecasted event (e.g., understand the rationale behind the forecast and the significance and potential impact of the event to mitigate). Aspects of HSCB knowledge include the PMESII (political, military, economic, social, informational, infrastructure) conditions in a region, as well as the goals, standards, preferences, and beliefs of groups and key influential individuals (e.g., leaders) in the region, and other key regional players and their objectives. Training for mitigation cultivates the special knowledge and skills that planners need to thoroughly understand applicable U.S. objectives and priorities when considering diplomatic, information, military, and economic (DIME) options for COAs, resources available to execute them, the effects of the COAs, and measures of effectiveness and performance.

Operators need many skills for mitigation and must be trained to acquire them, but we focus here on those skills most influenced by recent improvements in HSCB capabilities. All planners and analysts considering mitigation options must learn to rapidly ingest available information about the operational environment. To properly harness emerging HSCB capabilities, they must know how to use the tools, understand the quantitative and qualitative aspects of social science modeling, and recognize the benefits and limitations of the data sources used by HSCB tools.

To more clearly identify requirements for mitigation training, we consider the mitigation process from two perspectives: (1) the kinds of HSCB knowledge needed to perform mitigation analysis, and (2) the skills needed to incorporate the HSCB dimensions of a geospatial region into the planning process. We categorize these in terms of the development, analysis, and assessment phases.

The next section of this chapter presents a mitigation use case that offers a notional background for describing the knowledge and skills needed for each of the phases of mitigation. It discusses the three phases of constructing a Theater Campaign Plan (TCP), and highlights some emerging HSCB technologies beginning to have an impact on this process. Subsequent sections summarize the HSCB knowledge and skills required for each phase of mitigation. Finally, we discuss the objectives for training to support planners and analysts in developing the capabilities required to perform mitigation effectively.

2. Mitigation Use Case: Theater Campaign Plan

As an example of the skills and knowledge required from operators to perform mitigation, we describe the TCP**:** a strategic plan designed to mitigate instability and to achieve other desired end states in a Combatant Command's (CCMD's) area of responsibility (AOR). An AOR includes a number of countries that may exhibit considerable diversity. For example, U.S. Pacific Command (PACOM) spans 36 countries around the Pacific Rim, including Australia, China, and Fiji. Planning in the PACOM AOR is therefore a challenging problem that calls for considerable HSCB knowledge, skills, and tools (see Figure 1). U.S. goals in a geographic AOR include the prevention and mitigation of regional instability. For peacetime operations, the TCP and country plans represent longer range, multi-year allocations of resources to appropriate DIME actions.

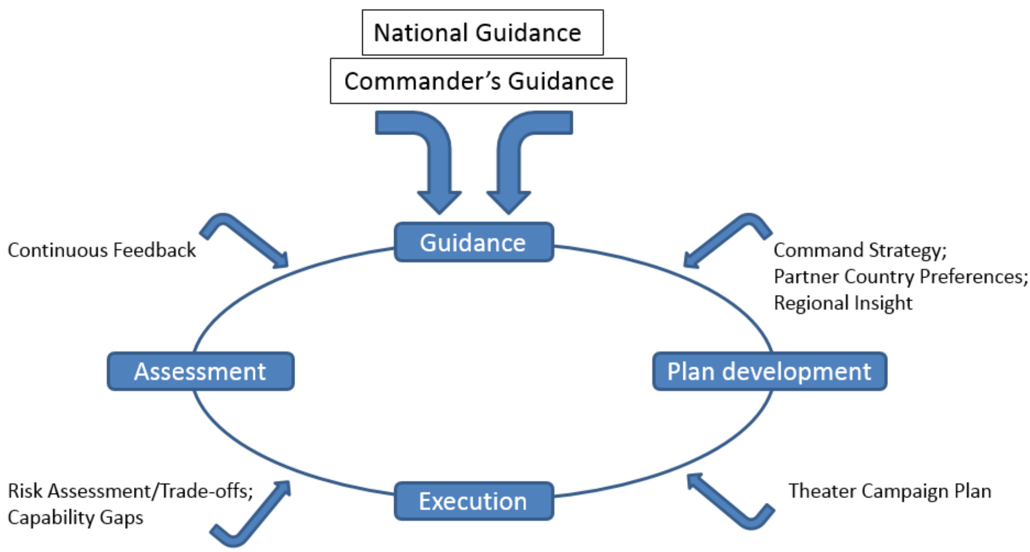

Figure 1. National Defense University model of the strategic planning process.

The TCP process not only reveals opportunities and requirements for additional automation[2], but also helps illustrate additional requirements for human competencies (knowledge and skills) that must be conveyed through training. The following description of the TCP is based on official planning guidance (Theater campaign planning, 2012) and on relevant discussions with CCMDs that

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[2] DARPA Integrated Crisis Early Warning System (ICEWS) effort (O'Brien, 2010; Kettler & Hoffman, 2012) was initially targeted to aid CCMDs to develop and assess the Theater Security Cooperation Plan (TSCP), a key part of the TCP that focuses on bilateral DIME actions such as joint training exercises between the U.S. and another country.

took place as part of the Defense Advanced Research Projects Agency (DARPA) Integrated Crisis Early Warning System (ICEWS) program.

Inputs to the TCP include global U.S. priorities as articulated in the Guidance for the Employment of the Force (GEF) and Joint Strategic Capabilities Plan (JSCP). The GEF specifies broad strategic theater end states, looking out 5 to 10 years. TCPs have a strategic focus on the longer term, rather than on a specific operation (e.g., a combat operation, relief for a particular disaster, etc.). They also emphasize planning for the "steady state" by describing DIME actions and resources required to make progress on longer term objectives, including keeping the peace by mitigating potential instability. TCPs are not static and must be updated if the situation in the AOR changes, for instance if resources become unavailable or a natural disaster occurs. For example, the 2005 tsunami in Indonesia required considerable attention and resources from PACOM, given the scale of devastation and the longer term potential for adverse impact on regional stability. TCPs require coordination across the DoD (e.g., individual services supporting the CCMDs), non-DoD U.S. Government agencies (e.g., the State Department, U.S. Agency for International Development), the individual countries in the AOR, allies, and nongovernmental organizations (NGOs). Many of those entities are involved in the actual execution of the TCP – for example, providing resources – with the CCMDs responsible for overall planning, execution, and assessment of the TCP.

An early task in TCP planning is COA development, which focuses on mission analysis and on assimilating high-level guidance from documents such as the GEF and JSCP, and includes identifying desired theater strategic end states projected 5 to 10 years in the future. The planners integrate guidance and supporting information into (a) intermediate military objectives (IMOs)[3] leading toward end states, (b) key planning assumptions, and (c) available resources. Intelligence support to TCP planners identify and describe threats and opportunities associated with desired end states, including regional PMESII factors, the potential COAs of countries outside the AOR and hostile countries inside the AOR, and transnational actors that may have their own interests and objectives in the AOR.

ICEWS forecasts of country instability, which provide early warning of potential hot spots where the TCP planners may need to consider COAs for mitigation efforts, represent one example of recent HSCB-enabled technology that can have an impact in the area of mitigation. Recent work on supplementing ICEWS forecasts with details automatically mined from ongoing monitoring of open media (newsfeeds, social media, etc.) and classified sources may provide additional guidance for refining TCP development by elaborating and verifying the actionable details of a potential instability event of interest (EOI). For example, understanding which groups in a country might be fomenting unrest and why they are doing so could help avoid an event by suggesting more specific and effective COAs that the TCP may identify with respect to a peacekeeping IMO.

[3] Examples of IMOs include building partner (country) capacities, gaining access, maintaining relationships, conducting security force assistance, supporting ongoing operations, etc. Like all military objectives, IMOs are ideally outcome- vs. process-oriented, time-bound, and measurable.

Mindful of the threats and opportunities in the AOR, the CCMD next develops a TCP around IMOs that contribute to the desired end states. Initially the ICEWS forecasting capabilities (iCAST) were intended to help CCMDs determine where to focus their TCP portfolios, given their objectives, repertoire of potential DIME actions,[4] and available resources.

COA development centers on assimilating guidance into the identification of a desired end state and a strategic plan for realizing that end state. Training for COA development must advance students' knowledge and skills in identifying a desired end state consistent with guidance, relevant objectives, and possible actions (i.e., potential COAs) to accomplish the objectives based on awareness of the current state and the expected impact of possible COAs. While most planning courses currently teach these fundamentals to some degree, they must be extended to incorporate emerging HSCB capabilities. For example, TCP planners should learn to better incorporate social science knowledge about the populations affected to increase the number of potential COAs that might achieve key objectives.

Determining the best COAs corresponding to TCP objectives requires analysis of potential COAs to project and assess the likely impact. Ideally, this includes modeling the actions to provide a deeper understanding of potential impact. Such modeling can be difficult, since the actions themselves may be ill specified. Their effects may be conditional (i.e., differ depending on the situation), extended in time, subject to interaction with the effects of other actions that overlap in time, or dependent on unknown factors. Some contemporaneous actions may be unknown (e.g., the DIME actions by other world powers with potentially competing agendas). Actions may have n^{th}-order effects that are neither well known nor easy to mine from incomplete or noisy historical data.

To analyze COAs for DIME objectives, planners must understand the impact an action may have on the operational environment (see Figure 2). The ICEWS project built Bayesian models based on the input of subject matter experts (SMEs), such as social scientists, country analysts, etc., to explore the impact of DIME actions. The key SME tasks included defining DIME actions (e.g., what constitutes an economic action such as "Provide Financial Aid"), eliciting contextual variables that determine the conditional effects of a given action (e.g., Action *X* can have one set of effects in Country *X* and different effects in Country *Y*), and "linking" variables that capture the effects of DIME actions (e.g., the change in rate of violent events in a country). For example, SMEs associated an economic action such as "Provide Financial Aid" with context variables such as the capacity of government, influence of trading partners, distribution/delivery mechanisms, etc. The SMEs correlated these context variables with effect variables, such as impact on Cooperation (e.g., level of cooperative events) and Discord (e.g., level of violent events).

[4] Possible DIME actions include activities such as visits by high-level personnel, bilateral conferences, bilateral training exercises, port visits (for diplomatic, show-of-force, and economic impact), medical assistance, engineering project assistance, etc.

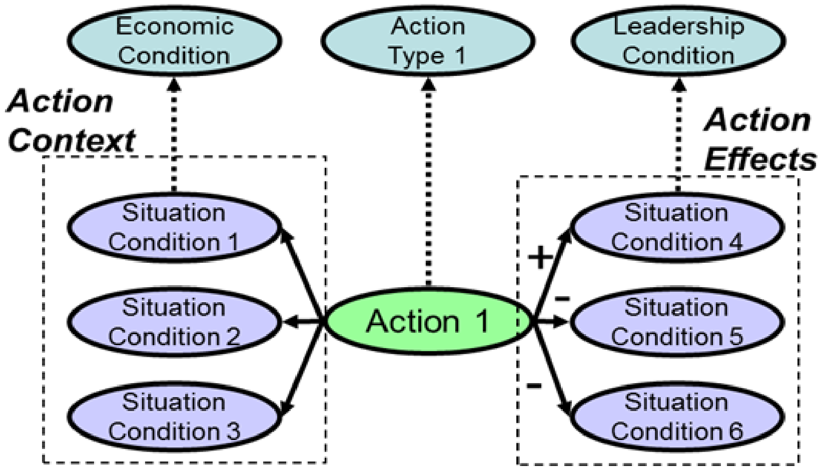

Figure 2. SMEs defined (a) the DIME action ("Action 1"), (b) relevant contextual variables ("Action Context"), and (c) effects of DIME actions ("Action Effects).

COA analysis assumes that the development phase has generated one or more potential COAs; the analysis then focuses on projecting and assessing the future impact of the actions defined in those COAs. Training for COA analysis must emphasize acquisition of knowledge and skills for identifying context variables relevant to the action and effect variables influenced by the action, understanding the relationship between the context and effect variables, and increasing awareness of sensitivities such as conditional or interaction effects. Advances in HSCB technologies, including “what-if” forecasting and variable identification, have built on some of the lessons learned from the intensive modeling exercises with SMEs, making the information more operationally accessible. To take advantage of these technologies, TCP planners need to be trained on HSCB models and other relevant tools.

COA assessment for TCPs often occurs in parallel with COA development, as different parts of the TCP may be in different stages of planning and ongoing execution. Assessment may be triggered by regular review timetables, commanders’ questions or directives, developing world events, emergent threats or opportunities, the completion (or failure) of DIME actions, execution of the TCP, etc. Assessment includes applying various measures to evaluate the performance of planned tasks/actions (i.e., did the action take place as planned?). For example, did a port visit occur or was it prevented by weather or other factors? Was the action only partially completed? If an action executed as planned, did it have the desired diplomatic, military, political, or economic impact, contributing to a higher level desired end state? For example, perhaps the port visit was designed to improve public support for the United States, but actually spawned anti-U.S. protests. Finally, the assessment must cover the cost of performance versus the effectiveness of the action: was the resource investment worthwhile compared to alternative actions?

Assessments require significant resources to capture the relevant information, analyze it, assimilate it, and archive it for future use. Assessments demand manpower, tools, and data, and should be performed in a timely fashion while information is fresh. Tools have typically lagged behind the need and have been limited to databases, spreadsheets, and other ad hoc methods that impeded information integration, sharing, and reuse. Typically it is easier to collect information pertaining to measuring performance (what was done) vs. measuring effectiveness (what was achieved in terms of actual vs. desired effects).

Operational deployment of capabilities such as those offered by ICEWS allows the user to leverage open media (e.g., news reports, social media,[5] and other sources such as financial market indicators) to augment information gathered by CCMD assessment staff (Sanchack, 2012). For many countries, these sources provide a wealth of indicators relative to the issues that concern the population of a country or city and their sentiment about those issues. News reports can provide useful indications regarding the effects of a DIME action. For example, while a port visit is ongoing, analysts can inexpensively detect protests or other reactions among the populace by examining news reports from multiple sources. This helps define metrics for assessing effectiveness of the current TCP and for building computational models of DIME actions in the future.

Training for COA assessment should enable students to gain knowledge and skills for evaluating COA execution; measuring COA impact based on indicators in HSCB knowledge, including analysis of open media; and assessing COA suitability in terms of resource availability and consumption, cost, and other measures.

3. Knowledge and Skills Requirements for Functional Mitigation Tasks

This section presents an initial analysis of the knowledge and skills needed to perform the functional mitigation tasks of COA development, COA analysis, and COA assessment. The discussion will guide training considerations by identifying the learning objectives that foster the requisite human competencies. In this section, we describe the knowledge that informs all areas of mitigation tasking and then decompose each mitigation task to identify the particular skills needed to perform them.

3.1. Knowledge for COA Development, Analysis, and Assessment

COA development, analysis, and assessment require similar kinds of knowledge, although each uses that knowledge in a unique manner. To perform mitigation tasks analysts need (a) social science knowledge resulting from integration of information sources such as population-centric information and sociocultural information, and (b) knowledge of modeling (including underlying theories and data) and model results.

Social science knowledge generated from population-centric information and sociocultural information describes the HSCB dimensions of the operational environment that are essential for

[5] Via the newer iSENT social media (Twitter, blog, etc.) ingest and analytic capabilities, which include sentiment and influence analysis.

mitigation tasks. Population-centric information details the demographics of the population, while sociocultural information characterizes the relationships among contextual factors and individuals or populations. This includes such information as where people are located in a geographical space, group associations, political or religious affiliations, economic conditions, social and cultural expectations regarding how people interact with their environment and each other, and how deviations from social norms (e.g., improper discarding of holy items, inappropriate interactions with respected or authority individuals) may affect social responses such as sentiment or mood. These data are critical for developing high-quality and effective COA alternatives. The alternatives built upon this HSCB perspective reflect an understanding of the commander's intent within the sociocultural context of the local population, which results in an accurate and effective design for realizing essential tasks and, ultimately, in mission success. The integration of these kinds of information produces social science knowledge that enables useful understanding of the correlations among contextual factors and their impact on the operational environment to support the execution of necessary actions for mitigation.

To effectively plan tasks to be performed within a geographic region, the deployed resources must understand demographic characteristics of the local population. For example, if the United States intends to provide food as aid to a particular region, planners must understand the relevant tenets of the population's religion (e.g., dietary or handling implications).

Social and cultural behaviors can indicate group norms, where these norms encompass the actions or interactions that individuals of a particular social or cultural group would expect from their environment. These kinds of interactions can be as simple as shaking hands when meeting someone or as complicated as understanding an inherent social hierarchy and sitting lower (i.e., closer to the floor) than a perceived superior. Understanding this type of information facilitates the use of other relevant data sources such as social media in order to extract supporting content that provides deeper awareness and understanding. Mitigation training needed to support the processing of HSCB knowledge during COA development must be based on access to both population-centric and sociocultural information. For example, geolocated blog posts that reveal the political perspectives of the people in an area can add depth to population-centric information describing the political demographics of that area. Social media offer a fertile platform for acquiring population-centric and sociocultural information supporting various kinds of HSCB knowledge. These media can be a valuable source of data for sentiment analysis – assessing the attitudes, emotions, sentiments, and opinions of a population – and mood shift analysis, which specifically considers the trends in sentiment or mood. Social media also aid in trust assessment of open source data. Trust is a key element in the effective functioning of groups.

To generate alternative COAs in response to a mission statement and a strategic approach, planners need the ability to understand what the data convey about the characteristics and configuration of a population, and what the models indicate with respect to the theoretical significance of data trends. Models that depict how particular factors influence the human, social, cultural and/or behavioral dimensions of a population help analysts to project an expected consequence based on an initial configuration of such factors and DIME actions. These types of modeling tools provide the knowledge necessary for better understanding the relationships among

contextual factors within the HSCB space and the impact those factors have on the stability of the operational environment. Exploring models and manipulating the factors they encapsulate allow analysts to (a) investigate and identify threats and opportunities and their effects on the desired end state, (b) recognize high-level objectives of parties external to the AOR that may contend or otherwise affect the strategic agenda of the CCMD, (c) project and evaluate future impact of changes in contextual factors, and (d) contribute to defining measures for assessment and prioritization of COAs.

HSCB models enable users to apply the massive and complex data in the HSCB space in order to present analysts with tractable content and enable them to easily and quickly identify relevant information. However, all models present a simplified view of the actual world. To effectively leverage a model, users must translate the model's representation of the world to fit the user's perspective. Understanding a model's output requires knowledge of the purpose and performance of the model and awareness of sociocultural elements of the environment such as population distribution and composition, cultural norms, or religious affiliations. Users' trust in the ability of a tool to help generate COAs will depend on substantiated evidence that the model enables a *valid* representation of the operational environment. Thus, intelligence and operational planning experts must be trained on how HSCB models represent the operational environment, and how to translate and leverage this content for COA development. This will aid users to interpret the model results, build trust in the model, and gain awareness of factors in the real world (based on model analysis) that are relevant to COAs.

Because HSCB models rely on sociocultural knowledge and theories, users must also learn that some models are more heuristic based (Moss & Edmonds, 2005) than the models currently applied to operations, which typically provide detailed representations of potential kinetic force-on-force outcomes. Nevertheless, these heuristic models still provide valuable operational insight.

Clear visualizations and model transparency are critical to training in COA development. Interpreting visual representations of model performance, forecasts, analysis, etc., must become second nature to the HSCB model user/COA developer in order to make the results optimally effective in assessing relevant HSCB content and model forecasts quickly. Training must take into account that many potential users will be qualitative vs. quantitative thinkers; good visualization tools must support a range of users with varied job functions and modeling and social science expertise (OSD, 2009).

3.2. Skills for COA Development

To mitigate or avert a potential crisis or event, planners must first develop COAs that counter the undesirable action and promote achievement of the desired end state. Once planners have analyzed the mission and generated high-level guidance to achieve desired theater strategic end states, the TCP identifies objectives (i.e., IMOs) that contribute to these end states and ultimately designates COAs intended to realize the TCP objectives. COA developers such as TCP planners must have the knowledge and skills to identify contextual factors relevant to realizing the desired end state; understand the potential COAs of friendly, neutral, and adversary nations and transnational groups both inside and outside the AOR; assimilate guidance into the identification and description

of a desired end state; and generate COAs with the expectation of realizing the desired end state. This should include the ability to describe threats and opportunities associated with that end state, identify relevant regional PMESII factors in the AOR, define objectives (i.e., IMOs) leading toward the desired end state, recognize key planning assumptions, and, finally, for each objective, generate COA(s) designed to realize the objective and determine the available resources for performing the COA(s).

COA development requires awareness and understanding of the desired or projected future. The following subsections identify the knowledge and skills required to perform each of the four high-level tasks comprising COA development. They then describe how these knowledge and skills translate into training implications for developing the awareness and understanding necessary to perform these tasks effectively.

3.2.1. Skills to identify contextual factors of consequence

Once the commander has set a high-level strategic agenda and characterized it in terms of a desired end state and objectives, a COA developer must extrapolate and identify aspects of the operational environment relevant to the agenda. These aspects consist of contextual factors that will aid in assessing the current state, forecasting the future state, and interpreting the impact of actions on the future state.

While the intelligence career field has built some expertise in these skills, the planning community (though supported by intelligence) typically consists of operators (e.g., Air Force pilots). Training for these individuals must cover emerging HSCB-enhanced mitigation tools (such as social science forecasting models). The ability to understand models includes the ability to observe and learn the relationships and factors presented by a model of an HSCB phenomenon. Planners can leverage this understanding to interpret and understand the model's results. For example, the iCAST component of ICEWS contains agent-based models (ABMs) of specific countries for specified EOIs. iCAST calibrates these ABMs to the current state of the modeled country and then executes them to produce multiple trajectories of potential future states of that country. The actions and interactions of the agents in the ABM that lead to each future state are based on rules and environmental conditions that describe the country and the sociopolitical theory guiding the ABM. For example, all of the ABMs developed for ICEWS stem from a generic political model that captures rules based on political theory for actions such as protest, rebellious activity, and religious violence. As planners recognize and comprehend the political theory at play in the ABMs and the country's environmental conditions framing the initial state of the ABM, the model output enables them to understand the variety of potential future states that the model generates and hence potential futures for the country in question.

Within the possible futures, analysts may identify threats or opportunities that may manifest themselves, as well as specific contextual factors that could result from underlying operational factors. For example, the model might predict high levels of protest that may indicate depleted resources or insurgent propaganda. Those operational factors could suggest a potential COA for mitigation. Planners also benefit from the ability to experiment with model input parameters, manipulating the model in order to determine how changes in input affect potential futures.

3.2.2. Skills to understand COAs of other countries

Concurrently, COA developers must consider what activities other countries are engaged in or are planning to leverage, exploit, or contend with that may affect progress toward achieving the desired end state. Potential COAs of transnational actors or influential countries both inside and outside the AOR will favor distinct, though possibly overlapping or competing, interests and objectives. Identifying and understanding potential COAs of influential countries or groups may require the type of knowledge described above for identifying relevant contextual factors, and definitely requires unique skills for identifying possible high-level strategic agendas of other parties that may have an impact on the strategic agenda of the CCMD.

Once an analyst has characterized the interests of external parties, distinguishing COAs for transnational actors or for countries inside/outside the AOR calls for the recognition of high-level objectives that may conflict with or otherwise affect the strategic agenda of the CCMD. The process for recognizing relevant factors is similar to the process for identifying contextual factors described in section 3.2.1, the process for mapping contextual factors to high-level objectives described in section 3.2.3, and the process of translating objectives to COAs described in section 3.2.4.

Once analysts have noted the contextual factors relevant to the CCMD's strategic agenda, they need the skill to leverage the model's capability to explore external factors that may have an impact on the contextual factors associated with the strategic agenda. After identifying these external factors, analysts must consider the interests of other parties in these external factors. Scenarios illustrating how the interests of transnational actors or other countries can affect external factors result in identification of third party agendas that could threaten or present opportunities for the CCMD's strategic agenda.

3.2.3 Skills to identify objectives

Planners must decompose high-level strategic guidance into tractable objectives that can be aggregated to realize the desired end state. Identifying these objectives and the assumptions that may underlie them is critical for developing valid COAs. HSCB-relevant skills must enable planners to translate strategic guidance into clear operational objectives and articulate the key planning assumptions within the context of the unique sociocultural elements of the particular target country/region.

HSCB modeling and model results have become increasingly useful in understanding the relationship between a desired end state and its relationship to the operational environment. For example, the desired end state of effective cooperation between the United States and Country X may be achieved through COAs that support various objectives, including developing pro-American sentiment within the population.

3.2.4. Skills to generate candidate COAs

Having accomplished the previous steps, COA developers must consider how to relate specific objectives to the possible COAs, identify the resources required for each COA, and prioritize the COAs. Consider the operational objective of eliminating the support base of a particular adversary. Planners might consider multiple COAs, such as military information support operations (MISO),

increased security in certain areas, kinetic attacks on known adversary command and control elements, and non-kinetic attacks on adversary propaganda sites. Current kinetic models, based on the principles of physics and on extensive information on how systems operate (e.g., integrated air defense systems), can give users confidence in the accuracy of their estimates. By contrast, HSCB systems use theories from areas of study such as sociology, anthropology, and psychology that are much less (if at all) grounded in physical principles, yet are still capable of providing valuable and relevant insights. While most operational planners are very familiar with kinetic principles, their understanding of social sciences is often anecdotal at best. As such, operational planners must learn when it is appropriate to apply HSCB models, and how to interpret the model results with respect to the degree of confidence the model merits within the context it is being applied.

3.3. Skills for COA Analysis

In the TCP use case, planners must model the actions involved in a proposed COA to determine how implementing those actions might affect the operational environment. Exploring how DIME actions may affect the variables input to a forecast model supports COA analysis. If a DIME action can be associated with a change in a model's input variables, the model will reveal how those changes affect the forecast probability.

Planners should assess the feasibility of a COA to determine whether the proposed action can accomplish the mission objective within the allocated time, space, and resources. To support COA feasibility assessments planners need the information and tools that enable them to model and assess resource requirements and the impacts of DIME actions and others.

During the COA analysis phase planners must also evaluate the acceptability of a COA. This analysis considers whether the benefits of the COA outweigh the expected costs in terms of such factors as losses of friendly forces, time, position, and opportunity. Acceptability analysis also ensures that the COA accommodates constraints such as rules of engagement for specific operating environments.

Wargaming offers an effective preliminary means of performing feasibility and acceptability assessments. Wargaming provides a context to identify the advantages and disadvantages of a COA, ultimately allowing for a comparison among COAs. The wargame iterates a process of action, reaction, and counteraction that fosters ideas and insights that inform preliminary validity assessments of potential COAs.

Wargaming for COA analysis may be entirely manual or computer assisted. Both forms require similar training regarding the development of tactical judgment and operational experience, but computer-assisted wargaming incurs the additional overhead of loading scenarios into the system and training users on the system. However, the versatility of computer simulations for supporting multiple scenarios mitigates this cost.

To perform COA analysis, the operator must investigate the impact that a particular action may have in a given environment. Models that facilitate "what-if" investigation—also known as hypothesis testing— of the scenario of interest in the operational area can assist this impact

assessment. For example, a model could help operators to answer questions such as “If we increased forces in this area, how would the adversary or friendly/neutral actor respond?” or “If the adversary took a particular action, what would be the most effective counteraction?”

3.4. Skills for COA Assessment

COA assessment includes Measures of Effectiveness (MOEs) for evaluating the accomplishment of the mission objectives and achievement of the desired end state (CJCSI-3170.01E, 2005). MOEs may consist of more detailed measures, specifically Measures of Performance (MOPs) and Measures of Suitability (MOSs). MOPs detail in quantitative terms how well a particular activity was executed; for example, whether a port visit occurred or was prevented by weather or other factors. MOSs relate to the feasibility of the COA within the operational environment, reflecting operational readiness or availability with respect to the intended action; for example, whether the available resources could support a port visit, or whether elements of the logistical infrastructure could not meet the resource requirements. For example, a MOP assesses the performance of a port visit, an MOS assesses the operational capability to support a port visit, and the MOE assesses the impact of a port visit on the overall mission objective in terms of diplomatic, show-of-force, and economic effects.

4. Implications for Training for Mitigation

Training for mitigation must lead to the development of HSCB-related expertise. As technology capabilities emerge that support the management of HSCB content for application to mitigation scenarios, the training community will learn more about what training specific to this context requires. One concern is that in order to train individuals for a specific mitigation task using HSCB data, it must be assumed that the individual has been provided with a degree of education. There is no clear documentation of what education is required for training in mitigation. Having preliminary knowledge and understanding of the HSCB context of the deployment environment provides each trainee with better, deeper awareness of the human-related forces at play in that environment so as to be able to better perform the task being trained. This section distinguishes between education and training expectations and describes recommended learning objectives for both with respect to mitigation. We also describe emerging technologies that support such education and training or technological gaps related to each learning objective.

4.1. Description of the Mitigation Training Space

> Cultural understanding doesn’t just help you achieve your objectives—it helps you discover what your objectives should be.
>
> — General Anthony Zinni (Rasmussen & Seick, 2012, p. 1)

While many breakthroughs in HSCB technology have the promise of fundamentally changing the military planning community’s approach to mitigation, military members will need to be trained on how to use the rapidly growing amount of information and new tools before the promise of better mitigation can be reached. Historically, formal U.S. military training for crisis mitigation based on cultural factors has focused on potential nation-state level reactions to blue courses of action.

More recently, mitigation training has taken a strong tactical focus involving individual soldier training in face-to-face cross-cultural contact. The tools and cultural information/understanding did not exist in the military to conduct operational-level mitigation training. Training articles are beginning to discuss an expanded view of the cultural training, to include such concepts as "culture-general capabilities" and "cross-cultural competence" (3C), but these ideas still focus primarily on mitigating tactical level activity that might cause unanticipated strategic consequences. (Rasmussen, Sieck, & Osland, 2010; Wisecarver, Ferro, Foldes, Adis, Hope, & Hill, 2012)

Even with a tactical training view, work remains to be done on defining the best approaches to improving the military's cultural understanding, and applying that understanding to mitigate undesirable outcomes. "Current efforts towards defining and scoping culture-general capabilities, or Cross-Cultural Competence (3C) include high level cognitive skills such as sensemaking and perspective taking (Abbe, Gulick, & Herman, 2007)—however, the field has yet to effectively characterize the cognitive processes that these skills entail." (Rasmussen, Sieck, & Osland, 2010, p. 2)

Though training objectives don't currently exist for the new portfolio of HSCB tools, each of the services has developed training for individual cultural understanding. For example, the Marine Corps Operational Culture And Language Training And Readiness (T&R) Manual (p. 21), training objectives include:

- Assess the attitudes among a foreign populace
- Assess the behaviors among a foreign populace
- Assess cultural considerations that affect the population's attitudes/behaviors
- Incorporate cultural considerations into plans and operations
- Develop TTPs
- Implement plans to target the desired attitudes/behaviors
- Monitor the effectiveness of plans targeting attitudes/behaviors
- Reassess the population's attitudes/behaviors
- Adjust operations

These training objectives are representative of how the services are training their planners and operators to consider sociocultural factors. These objectives are often taught as thought exercises, and rarely extend past an initial understanding of potential first order effects. Some more complex capabilities, such as red teaming, are taught to limited groups and begin to train military personnel on how adversaries are likely to respond to blue courses of action. The objective of red teaming is to "avoid groupthink, mirror imaging, cultural missteps, and tunnel vision in plans and operations" (University of Foreign Military and Cultural Studies, 2011, p. 1). These techniques provide great value to operational planning, but seldom extend beyond considering the stated adversary into considering the reaction of the surrounding population.

Innovations such as those described here are designed to support operational level tasks such as course of action generation, etc. Today's HSCB tools bring the capability of not only considering the

adversary, but of multiple facets of the local population. This will radically increase the number of elements of mitigation that can be considered by planners, if the tools are made more widely available and properly trained. Training will need to include not only formal courses, but also integration into exercises and Master Scenario Event Lists (MSELs) and exercises.

4.2. Mitigation Education and Training: Bridging the Gap

Before we can expect a trainee to be able to perform a mitigation task which in the real world must be performed in the face of uncertainty, we must first educate the trainee to better understand and act in an uncertain space. As a result, training for mitigation must be preceded by education. To develop education curricula to support mitigation training, "we must cultivate an environment in which we teach our soldiers how to think and adapt, not what to think." (Burton, Nance, & Walton, 2011, p. 1) In other words, mitigation education must build "a culture of flexibility" in thinking to support the training of specific mitigation tasks (Burton, Nance, & Walton, 2011).

For example, in order to effectively mitigate scenarios dealing with information about events or actions taking place in a foreign environment, the user of the system must have received education previously. In particular, the kind of education relevant to such a context may be education in the norms and traditions of the associated culture, as well as education in the understanding and awareness of cognitive biases. This education background prepares the user to be able to mitigate uncertainties that may arise from being informed of events or actions contrary to what the user is accustomed to in his/her personal cultural experiences.

In this section, we will identify learning objectives for education for mitigation. Strategies that have been employed for achieving such objectives are identified. As tools to support mitigation have been developed, the question of how much education is needed to support use of the systems is an open question. If too much education is required, then the system requires over-specialization of its users, and cannot be sustained. For example, if a user needs to have a PhD in statistics to be able to interpret results presented by these systems or to understand the significance of events in a data set, then the system will not be able to be effectively employed by the target users. If the user is unable to understand what the system is doing or how it works, then the lack of confidence in the results will undermine the significance of the content. For example, if a mitigation support system is indicating the decreased likelihood of a violent event, but the system is not able to communicate to a layperson user what factors are leading to the assessment, then the user is less likely to trust the analysis and hence less likely to feel comfortable leveraging the information for building COA. Ongoing work is attempting to exploit visualization and automation techniques to support verification and validation of models and data to lower the education threshold for using these systems. For example, the Model Evaluation Selection and Assessment (MESA) project under the Office of Naval Research is investigating innovative verification and validation techniques for HSCB models to support the transparent and accessible understanding of how HSCB models work, the data they use and produce, and the theoretical principles that drive the model (Ruvinsky, Wedgwood, & Welsh, 2012).

This section describes recommended objectives for education and training for mitigation, as well as emerging technologies that support such training or technological gaps related to each learning objective.

4.2.1. Education learning objective #1: Understanding human dynamics

Sociocultural sensemaking for mitigation requires understanding “human dynamics,” defined as “the actions and interactions of personal, interpersonal, and social/contextual factors and their effects on behavioral outcomes” (Defense Science Board, 2009, p. vii). In the HSCB domain, human dynamics propel change over time. Factors that influence human dynamics include economics, religion, politics, and culture. Developing skills in understanding human dynamics entails acquisition of two distinct, yet complementary, perspectives: a culture-general perspective on human behavioral tendencies, and a culture-specific perspective in which knowledge of these general behavioral tendencies is applied to a specific cultural context to develop an understanding of a particular culture.

Human Behavior Models (HBM) are used within simulations for training in which the task being trained requires understanding of other people, either individually (e.g., human psychology) or in a population (e.g., sociology), for decision making. They provide variations in human behavior in order to produce a more realistic experience for the trainee (Wray & Laird; 2003).

The use of HBM to establish the background context to training simulations makes it clear that education of the dynamics of human behavior is a pre-requisite to such training scenarios including scenarios relevant to mitigation where decisions are being made that impact populations.

4.2.1.1. Education for human behavior awareness

Education to foster awareness regarding human behavior must familiarize the trainee with the cultural factors that influence decision making at the micro level, as well as the kind of macro-level behaviors that emerge from these micro-factors. For example, ethnic diversity is the property of a geographical region and is described by having a population in which wide variety of races are found. In this example, the racial status of the individual contributes to the ethnic diversity of an area, which in turn impacts aspects of the environment which influences an individual’s experience. According to Kanbur, Rajaram, & Varshney (2011, p. 149), “The daily life of families, neighborhoods, regions and countries is influenced by ethnic diversity.” Various research projects hypothesize a positive association between ethno-linguistic fractionalization index (ELF; a measure of ethnic diversity) and the probability of civil war (Collier, Elliott, Hegre, Hoeffler, Reynal-Querol, & Sambanis, 2003). Education for human behavior awareness must leverage various disciplines, including psychology, sociology and anthropology, to name just a few.

Computational social science (CSS) models and HSCB data work to support an understanding of culture-general processes of human dynamics. Worldwide ICEWS (W-ICEWS) has a modeling and forecasting component called iCAST that leverages CSS models and HSCB data to predict events of interest. Though shown to be useful and produce interesting and relevant content, a significant challenge to this forecasting capability is the presentation of the sophisticated computational models and analyses to laypeople. To promote confidence in the iCAST models and forecasts, the

development team built a transparency capability that allows the user to explore the factors considered by the models and the relationships between the factors and the forecasted results. The transparency capability not only contributes to the user's awareness and understanding of how the model works by exposing the variables used by the models and allowing the user to change the values of variables to explore "what-if" scenarios, but also provides insight into the sociological implications of the model. Recent versions of iCAST leverage elements of the MESA program capabilities (Ruvinsky, Wedgwood, & Welsh, 2012), which provide techniques and tools to support the verification and validation of HSCB models.

4.2.1.2. Education for cultural awareness

Cultural Awareness as Cross-Cultural Competency (3C) is defined by Selmeski (2007, p. 12) as "the ability to quickly and accurately comprehend, then appropriately and effectively engage individuals from distinct cultural backgrounds to achieve the desired effect, despite not having an in-depth knowledge of the other culture." This competency goes beyond developing verbal communication skills for interacting with a particular culture, and toward developing culture-general knowledge as a framework for interacting with many different cultures. Understanding how culture influences human behavior is a first step toward understanding aspects of human dynamics in general, but real-world contexts are always culture specific. For example, the culture-general recognition that norms, beliefs, and customs influence the behaviors and interactions of individuals, groups, and societies helps analysts to identify or instantiate the norms, beliefs, and customs that prevail in a particular culture of interest. Analysts can then begin to reason about the impact of these instantiations on the behaviors and interactions of the individuals, groups, and societies in that culture.

Various technologies are being developed to support training in culture-specific awareness. For example, simulation environments for cultural training such as the Virtual Cultural Awareness Trainer (VCAT) have been shown to improve cultural-specific awareness (Johnson, Friedland, Schrider, Valente, & Sheridan, 2011). In fact, U.S. Southern Command has designated the VCAT as "Mandatory Training" for various culture-specific exercises (Alelo - Evidence of Effectiveness, 2013).

4.2.2. Education learning objective #2: Awareness and diminishing of cognitive bias

The term "cognitive bias" refers to subconscious errors that humans make in processing information. Such bias can lead to irrational or illogical actions. Trainees must learn to recognize cognitive bias in two contexts: (1) how cognitive biases affect the interaction of populations within the AOR, and (2) the trainee's own susceptibility to such biases as they evaluate potential COAs. Becoming aware of these cognitive vulnerabilities is a first step toward mitigating them.

4.2.2.1. Education to recognize evaluation biases

Understanding the benefits and limitations of data sources used by HSCB tools helps planners to evaluate the evidence presented by these tools. People are susceptible to a variety of extraneous influences when determining the evidence to rely on and how to interpret that evidence. Significant cognitive biases that can arise when evaluating evidence include confirmation bias, in which people place disproportionately great reliance on information that supports their own

beliefs or conclusions. HSCB data often describes aspects of human existence about which all people have ideas, opinions, and guiding principles or hypotheses. Analysts must be very careful to weigh the data objectively, and not to succumb to “the natural tendency of human beings to see what they expect to see” (Reese, 2012, p. 1261).

People are also subject to vividness bias, in which compelling, concrete, and personal information has a greater impact on the evaluation of a situation than more relevant, but abstract, information such as statistics. Vividness bias plays a role in assessing HSCB data because information garnered from HSCB sources such as social media often communicates memorable personal experiences in emotionally charged language (Heuer, 1999). Another form of bias, the anchoring effect, means that “focusing attention on a single option may lead the decision maker to neglect potentially valuable alternatives” (Missier, Ferrante, & Costantini, 2007). Planners must give consideration to all relevant and viable alternatives in the context of a decision problem.

As Keren (1990) posits, there are “cognitive pills for cognitive ills.” The term “debiasing” describes any technique used to prevent or mitigate cognitive biases. These techniques include evidence lineup, which may mitigate the anchoring effect by specifying a “lineup” of possible alternatives to consider, and competitive self-regulation, in which analysts compete with each other to produce analytical products free from cognitive biases. An emerging technology designed to identify and mitigate cognitive biases in analysts comes from the Intelligence Advanced Research Projects Activity’s (IARPA’s) SIRIUS program, which uses Serious Games techniques and technologies to train participants to recognize and mitigate various cognitive biases.

4.2.2.2. Training to recognize cause and effect biases

When using HSCB data and models to perform COA mitigation, analysts must make judgments about cause and effect as they identify possible COAs that would lead to the desired end state, analyze COAs to understand how causal factors impact the current state, and assess the utility, viability, and affordability of each COA. Perceptions about cause and effect can be influenced by centralized direction bias, which leads people to attribute effects to coordinated actions or conspiracies rather than to accidents, mistakes, or coincidence. In addition, analysts may assume that causes and effects are proportional to each other. In other words, large effects must have large causes. The training debiasing techniques described in section 4.2.1, such as using lineups, can help trainees to counter cause and effect biases.

4.2.3. Training learning objective #1: Develop assessments of HSCB dimensions of foreign populace

The first training learning objective one needs to achieve in order to perform mitigation is to explore the data describing the foreign populace in question. As an example of the kind of training that supports this objective, we will present the iTRACE and iCAST components of the W-ICEWS suite, and describe the training initiatives conducted for these components. ICEWS was designed to forecast instability events for countries in an AOR. ICEWS consists of various components designed to support the visualization and understanding of data and forecasts generated by the ICEWS system. ICEWS is composed of three modules: iTRACE, iCAST and iSENT. Both iTRACE (ICEWS

Trending, Recognition & Assessment of Current Events) and iCAST (ICEWS Forecasting) have been demonstrated and trained to operational users.

4.2.3.1. Task 1: Identify, explore and analyze data relevant aspects of HSCB perspectives of a foreign populace to be investigated with respect to a mission objective.

The primary goal of iTRACE is to provide a fully automated capability to monitor political activity around the globe. This is accomplished by automatically converting news reports into structured indices that reflect the character and intensity of interactions between key leaders, organizations, and countries. The iTRACE system provides a data-driven view into *who* is doing *what* to *whom, when, where* and *how*. The system is based on open-source reporting from a large number of major and regional news services. iTRACE processes these news reports to extract the character and intensity of interactions between entities such as leaders, organizations and countries. The processed content may then be used by computational models to discover, identify and explore trends and patterns, and ultimately indicate potential of impending violence, crises or conflicts.

The training goal was to prepare the operational users at USPACOM to use the iTRACE system to meet the command's needs for HSCB information, such as providing information on event trends in countries of interest or interaction trends between countries or actors over time. Many of the learning objectives of the training dealt with being able to use the iTRACE system itself, such as navigating and using the iTRACE interface, but there were learning objectives designed to teach users how to aggregate content and generate visualizations of content that support a particular HSCB informational need. It is important to note that the iTRACE training packet assumed that the users had previous education regarding aspects of the human, social, cultural and behavioral domains being investigated, such as education in human dynamics, both general and specific to the region in question, giving the user awareness and understanding of what HSCB information is relevant to the mission context. This education allows the user to identify aspects of the investigation that he or she will use to configure the iTRACE analysis, such as what cultural or religious groups are of interest? What leaders or organizations are relevant? What kinds of events or intensity of events are most interesting?

The iTRACE training was broken down into three scenarios. The first consisted of a demonstration of the system; the second allowed the trainees to reproduce the analysis that we demonstrated in the first scenario; and the third scenario posed questions to the trainees for which they used the iTRACE system to answer. These questions were decomposed into three categories in which the trainees were to investigate (1) activities between actors (e.g., what activities in the last 10 years involved Philippines towards the United States?), (2) event filtering (e.g., find events that involved Philippine military activity toward insurgency groups between Jan 2001 and Oct 2009), and (3) actor filtering (e.g., determine what recent events involved the president Gloria Arroyo of the Philippines).

4.2.3.2. Task 2: develop relevant, data-driven assessments based on HSCB data and tools that capture aspects of a foreign populace relevant to COA development

iCAST provides forecasts of the likelihood of the occurrence of events of interests (EOIs), namely domestic political crisis, ethnic/religious violence, insurgency, international crisis and rebellion and

the key factors driving them. The primary objective of iCAST is to provide human, social, cultural and behavioral awareness to the user regarding a forecasted country state. This is accomplished by aggregating the forecasts of multiple independent HSCB models to create a single, aggregate forecast that is more accurate that any one single model. By integrating improved versions of best of breed models from multiple perspectives, iCAST achieves more accurate, precise forecasts than any one model alone.

The iCAST training packet had four training objectives: providing the trainee with the ability to

- View forecasts for different countries and EOIs (e.g., what is the anticipated probability of a specific EOI for a particular country at a future point in time?)
- Analyze aggregate model forecasts with respect to individual model contributions (e.g., how accurate are the models that are contributing to the aggregated forecast?)
- Analyze specific model forecasts with respect to underlying data parameter contributions (e.g., what are the key factors that contribute to the likelihood of a particular EOI occurring, or not occurring, for some country?)
- Explore data parameter sensitivity within a specific model forecast (e.g., what might influence the probability of EOI occurring, or not occurring, for a particular country?)

iCAST training guided trainees through the navigation and use of the various visualizations and content provided in iCAST to answer questions such as those presented above.

Once data has been explored and a knowledge and awareness of the space has been established, courses of action may be developed to realize mission objectives while regarding the human, social, cultural and behavioral dimensions of the operational environment.

4.2.4. Training learning objective #2: Red teaming

The process of red teaming provides alternative options to a decision. By generating alternatives, potential improvements in decision making are exposed. According to University of Foreign Military and Cultural Studies (UFMCS, 2011, p. 1), “Red teaming is a structured, iterative process, executed by highly trained, educated, and practiced team members that provides commanders an independent capability to fully explore alternatives to plans, operations, concepts, organizations, and capabilities in the context of the operational environment.” Red teaming supports the decision making personnel in seeing the operational environment from varying perspectives including that of adversaries or coalition partners.

4.2.4.1. Task: challenge COAs by questioning assumptions, patterns, analysis, etc.

By questioning various aspects of a COA, red teaming can generate important analytical perspectives that the team may have previously overlooked. These perspectives include alternative analysis, consideration of other entities on the battlefield, identification of gaps or vulnerabilities, identification of sequences of events, and identification of measures of effectiveness. Red team training is conducted at UFMCS at Fort Leavenworth. According to U.S. Army Training and Doctrine Command, (2013, p. 6), “The basis for Red Team success relies on education and training grounded in theory, doctrine, cultural anthropology, the operational environment and focused Red Team techniques.”

The curriculum at UFMCS is organized around five themes:

1. Critical and creative thinking
2. Red Team techniques (e.g., negotiations, group dynamics)
3. Understanding how culture impacts the operational environment
4. Understanding the critical variables found in the operational environment with respect to trends and interrelationships, and
5. Western, non-Western and non-military theory

According to the University of Foreign Military and Cultural Studies (2011), there are various techniques and procedures that support the development of red teaming capabilities including a nine step cultural methodology which promotes understanding of a foreign culture. The cultural analysis produced by the nine steps provides a perspective known as the "four ways of seeing," namely, "how X views itself," "how Y views itself," "how X views Y," and "how Y views X." The nine steps are:

1. Establish a base line of understanding by examining the four ways of seeing
2. What defines the Social System? (roles of family/tribe and ways of ascribing/acquiring status)
3. What are the sources of power?
4. What are the critical narratives of the cultural history?
5. What is the role of the formal and informal economy?
6. What cultural forms and semiotics are endemic to the society?
7. What sociolinguistics are evident?
8. What are their core emotional beliefs?
9. In what ways does the collected data shape how Y thinks?

Red Team courses are taught at UFMCS as seminars taught by academic and subject-matter experts. Training includes case studies for developing "best practices" capabilities.

5. Conclusion

Emerging technologies relevant to mitigation have the potential to improve planning, but require significant enhancements to current operational training. The knowledge needed to perform mitigation spans human dynamics, DIME actions and their potential impact on population-centric objectives, and ways to counter cognitive biases. To develop the necessary skills and knowledge, analysts and planners should receive training in human behavior awareness (a culture-general approach) and cultural awareness (a culture-specific approach). Training should also enable users to assess the impact of DIME actions on the operational environment and human terrain, discern threats and opportunities associated with the operational environment, identify planning assumptions, and recognize and minimize various biases in processing information.

Current science and technology can support training in these skills. Still, many training gaps exist, and the continued development and fielding of HSCB mitigation capabilities make innovations in training of the skills and knowledge needed to perform COA mitigation tasks imperative.

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The past several years have seen significant advances in research and development across the human social culture behavior modeling domain. In order to document and share these advances, The MITRE Corporation has produced *Sociocultural Behavior Sensemaking: State of the Art in Understanding the Operational Environment.*

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This edited volume features chapters authored by experts in sociocultural behavior sensemaking across four operational capability areas: Sociocultural Understanding, Detection, Forecasting, and Mitigation. Each of the four sections dedicated to an operational capability area contains four chapters which focus on Data Processing, Computational Modeling, Visualization, and Training. These chapters highlight examples of recent advances, discuss the science and technology gaps, and propose strategies for incorporating recent advances into operational use for each of the capability areas.

This book raises awareness about emerging technical capabilities for operational communities. In doing so, it also provides the research and development funding community with a map of technology gaps that call for future investments to transition these capabilities to the field.

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